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Exploring decomposition of household items as an inexpensive, yet scientifically-robust, tool for assessing soil health

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Exploring decomposition of household items as an inexpensive, yet scientifically-robust, tool for assessing soil health

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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ABSTRACT

Soil health has emerged as both a movement in sustainable agriculture, and a framework for monitoring provisioning of soil ecosystem services. To increase interest and adoption of soil health promoting practices (SHPPs), we must make soil health more accessible to land managers by making soil health indicators less expensive, more informative, and less time-consuming. This study compares the proportion of decomposition (measured as percent mass loss) of green tea, rooibos tea, cotton underwear, and birch craft sticks, which are common household items, to traditional biological soil health indicators. My objectives were to 1) validate decomposition as an indicator of soil health by relating it to traditional indicators and maize yield, and to 2) evaluate the ability of traditional and decomposition indicators to detect differences between SHPPs and conventional practices.

I found that while decomposition indicators were often not related to traditional indicators of soil health, green and rooibos tea decomposition was positively correlated with maize yield, even when decomposed for just four days. In addition, decomposition indicators were able to detect differences in SHPPs at least as well as traditional indicators of soil health. Short-term decomposition of rooibos tea, in particular, showed high 'signal' (i.e. treatment effect) and low 'noise' (i.e. variability), and performed better than all traditional biological soil health indicators measured in this study. Based on my findings, measuring decomposition of household items was not only inexpensive and easy to use, but also comparable with traditional indicators of soil health with respect to their 'signal versus noise', or their ability to detect magnitude of effect of a SHPP compared to spatial variability. This suggests that decomposing household items shows promise as an inexpensive and scientifically-robust method for citizen scientists to measure soil biological activity, which is an important aspect of soil health. My data

further supports educational and outreach benefits of decomposing common household items with citizen scientists, and suggests this method of measuring biological activity could promote synergy between the soil health movement and scientists measuring change in soil ecosystem services.

CHAPTER 1. INTRODUCTION: DECOMPOSING COMMON SUBSTRATES TO ASSESS SOIL ECOSYSTEM SERVICES – A RETROSPECTIVE AND PROSPECTIVE REVIEW

1.1. Introduction

One of the substantial challenges humanity faces is sustainably meeting the needs of a growing population on increasingly limited arable land. The global population is expected to increase to 9 billion by 2050 (Bongaarts, 2009), a large proportion of potentially-arable land has already been converted to agriculture (Doran, 2002), and soil ecosystem services we depend on for food production and a sustainable planet have been depleted by poor management of existing arable land (Lal, 2010). Thus it is critical that production of food, fiber and fuel must not come at the cost of soil ecosystem services or what is now called soil health. Converting natural land to cultivated, highly-managed landscapes has decreased soil organic matter by 10-59% (Guo and Gifford, 2002) and concomitantly depleted soil ecosystem services these natural soils once supported (Kibblewhite et al., 2008; Tscharntke et al., 2005). The question is: can we recover these soil ecosystem services, or restore soil health, and still maintain high levels of productivity?

In order to meet this challenge, we will need indicators to monitor soil health; and these indicators must meet several criteria. They must be i) robust and based on linkages to soil ecosystem services, ii) within an acceptable range of variability and deliver repeatable results, iii) sensitive to management changes, iv) able to offer insight into how to correct deficiencies, v) easy to use, and vi) inexpensive and accessible (Doran and Zeiss, 2000; Morrow et al., 2016). These last criteria – easy and inexpensive – are critical in order for a soil health indicator to be widely adopted by land managers.

Measuring decomposition of litter or residue is straightforward – subtract mass of residue after incubation in the field from mass of residue at the beginning for mass loss as decomposition. It is relatively inexpensive compared to both commercially-available soil health tests and soil measurements at research institutions. This review will summarize uses of decomposing manufactured, household items to measure decomposition, and more importantly, how decomposition of these items may be used as an indicator of soil health. Here I define soil health as a soil's continued capacity to maintain several ecosystem services like nutrient-supplying power, carbon sequestration, and greenhouse gas mitigation.

1.2 Past Use of Household Items as Common Substrates for Decomposition

Decomposition is the process of organic matter breakdown and transformation to smaller, more stable forms, and is facilitated largely by soil fauna and saprophytic microorganisms. These decomposers, along with climate and litter quality, are the primary regulators of the decomposition process (Bradford et al., 2016; Meentemeyer, 1978; Swift et al., 1979, Fig. 1.1a). Decomposer organisms are tightly linked to many important ecosystem services that are central to soil health – like nutrient cycling and carbon sequestration. These soil ecosystem services are a byproduct of decomposer organism activity (Berg and McClaugherty, 2008), making decomposition an excellent candidate as a proxy for soil health.

Using decomposition is attractive for its simplicity, mostly because it is an integrated measure over time rather than the single "snapshot" approach used in soil sampling and analysis at one point in time. In order to simplify the technique further, some studies use standardized and widely available decomposition substrates. Such substrates have the added benefit of not requiring much extra quality control, being relatively inexpensive, and thus encouraging participatory science through their accessibility and ease of use.

Examples of standardized decomposition substrates used to measure soil functions include cotton and cotton-derived cellulose filter paper (*Gossypium hirsutum*), birch wood (*Betula spp*.), and tea leaves (*Camellia sinensis, Aspalathus linearis,* Table 1.1). One of the first popular substrates was cotton via the cotton strip assay (Latter and Howson, 1977a; Springett, 1971). This method, along with filter paper is often used by soil ecologists to observe differences in decomposer communities (Barel et al., 2019; Deacon, 1985; Gillespie et al., 1988). Wood is another frequently used decomposition substrate. Manufactured birch wood sticks, known as tongue depressors or popsicle sticks, are often favored in forested ecosystem studies due to high production of wood in these systems. Keuskamp et al. (2013) used Lipton green and rooibos tea leaves to examine decomposition rates and litter stabilization globally in a variety of ecosystems. Since Keuskamp et al. (2013), many researchers have subsequently compared the decomposition of the same two teas in a wide variety of ecosystems and for different purposes.

One primary reason for using manufactured, household items in decomposition studies is to have a standardized substrate. Often researchers use standardized substrates in addition to native litter from the ecosystem to provide a baseline for comparison amongst different ecosystems or to eliminate the "home field advantage" (Brown, 1988). To this effect, using a standardized substrate also allows for broad comparisons across varied ecosystem types and even biomes (Didion et al., 2016; Djukic et al., 2018; Tiegs et al., 2013). In most cases, standard substrates are also more cost- and time-effective than the alternatives, which can make measuring decomposition easier.

Soil ecologists have used manufactured, common decomposition substrates for a wide range of objectives. Some studies have used them to make predictions about the impacts of climate change (Althuizen et al., 2018; Mueller et al., 2018). Others have used them for

understanding the impact of environmental factors, such as nutrient availability and community composition, on decomposition in aquatic ecosystems (Seelen et al., 2019; Tiegs et al., 2013; Whigham et al., 2017). Other uses include determining the effects of invasive species on soil biology (Enoki and Drake, 2017; Helsen et al., 2018), measuring changes in soil decomposition rates due to the environment (Becker and Kuzyakov, 2018; Elumeeva et al., 2018; Proctor et al., 1988), examining extracellular enzyme activity in relation to decomposition (Sagar, 1988; Sinsabaugh et al., 1992), and measuring decomposition in extreme environments (Mikola et al., 2018; Tresch et al., 2018; Wynn-Williams, 1988). An additional common use is in agroecosystems where researchers are interested in comparing biological activity as affected by various agricultural practices such as tillage (Buchholz et al., 2017; Houben et al., 2018), cover crops (Barel et al., 2019; Sievers and Cook, 2018), herbicides (Zaller et al., 2018), or fertilizer rates (Poeplau et al., 2018).

1.3 The Potential of Decomposition as a Soil Health Indicator

1.3.1 Decomposition as affected by soil biology, nutrients, and carbon

Climate is widely accepted as the dominant regulator of decomposition, followed by litter quality (Meentemeyer, 1978; Swift et al., 1979; Wall et al., 2008). The role of decomposer organisms is often acknowledged, but it is typically assumed that since their activity is regulated largely by climate and litter type, and since they are fairly ubiquitous in the soil ecosystem, they achieve functional redundancy regardless of specific community composition. However, some work suggests that decomposer organism community structure or activity warrant more substantial consideration in research and models (Bradford et al., 2016; Grandy et al., 2016; Reed and Martiny, 2007; Strickland et al., 2009). Consideration of decomposer communities is probably nowhere more important than in agroecosystems where land managers control the litter

quantity and quality of litter inputs (i.e. residue), and decomposer organisms can be highly sensitive to management practices (Frey et al., 2000; Ladd et al., 1994; Powlson et al., 1987, Fig. 1.1b).

Outside of climate and residue quality, the relationship between the decomposition process and the microbial community is also largely determined by the quality of soil habitat they reside in and availability of resources. Soil structure and pore space are critical to harboring large and more diverse decomposer communities (Negassa et al., 2015; Tecon and Or, 2017); but the quantity and quality of mineral soil organic matter available also shapes the decomposer community structure (Li et al., 2018; Schnecker et al., 2014). Both of these are affected by management decisions in agroecosystems, which in turn affects decomposition of new residue inputs – resulting in a decomposer feedback effect (DFE, Fig. 1.1b).

There are multiple ways human management can result in a decomposer feedback effect, but probably the best examples of this decomposer feedback effect are studies from crop rotations. Take for example a crop rotation versus monoculture cropping system; even though soils might be under the same crop at any given point in time when the rotation is in the same phase, they have different histories of quantity and quality of crop litter inputs. This legacy of input history changes the trajectory of how new crop residues from that year are decomposed (Barel et al., 2019; McDaniel et al., 2014a). Other studies have demonstrated that decomposition of identical inputs changes with different starting decomposer communities as affected by agricultural management practices like no-tillage and restoration of grasslands (Wickings et al., 2012), and that different decomposer communities perceive litter quality differently based on their past resource inputs and current community structure (Strickland et al., 2009). These findings clearly indicate that the soil context, or soil microbial community and habitat (including

resources available to them) play a significant role in the trajectory of residue decomposition in agroecosystems. Generally speaking, greater overall microbial biomass often leads to greater decomposition as measured by substrate induced respiration (McDaniel et al., 2014a; Wardle et al., 1999), but microbial community composition (e.g. bacteria to fungi ratio, forest community vs. grassland community etc.) can greatly affect the amount and speed of decomposition of a given residue as well (Barel et al., 2019; Strickland et al., 2009). Thus measuring decomposition is a proxy of the size/composition/activity of the decomposer community, habitat quality, and the quantity/quality of the resources available to this community.

1.3.2 Measures of decomposition and links to soil health

There are a number of different ways to measure decomposition depending on the substrate being used, and the information sought. When using a cotton substrate, tensile strength is often the preferred variable of interest, and is tested using special tensile-testing machines (Latter et al., 1988). Wood decomposition studies often use mass loss as their measure of decomposition, but a few use wood strength loss, similar to tensile strength loss in cotton (Jurgensen et al., 2006) or change in wood density (A'Bear et al., 2014). Litter bag studies, including tea bag studies typically use mass loss (Barel et al., 2019; Bärlocher, 2005). Another approach is to measure the rate of decomposition using mass loss at multiple time points (Enoki and Drake, 2017; Keuskamp et al., 2013; Tóth et al., 2018). While measurement of decomposition rates is more informative than mass loss at one time point, the labor involved does begin to preclude citizen science applications.

A more recent approach is to use the decomposition of more than one substrate to derive an index for the decomposition rate (Keuskamp et al., 2013) or potentially for other purposes. In agroecosystems, we are interested in determining the 'signal' or change due to a management

practice that emerges through the 'noise' or natural variability in soil biology and climate. Using an index of two substrates may eliminate some of the variation and overarching climate effect, which is typically not a factor of interest for soil health studies. Climate contributes variability, or 'noise', and with soil health we are trying to minimize noise and detect a management signal. In one study, there was a consistent relationship between the decomposition of teas of differing quality, as determined by C:N ratio and carbon complexity, and temperature (Keuskamp et al., 2013). Lipton green tea (C:N = 12) and Lipton rooibos tea (C:N=43) decomposition both increased at higher temperatures, but the relative difference in total decomposition between the two remained approximately the same. Similar lack of a interaction between residue quality and temperature effect on decomposition has also been found elsewhere (Hobbie, 2005).

In support of using two substrates of differing quality to detect differences in soil biological activity, McDaniel et al (2014) used an incubation study combining 12-years of crop rotation history and a wide range of residue quality (at constant, optimum soil temperature and moisture). These researchers demonstrated that soils from a monoculture and complex crop rotation decomposed a high-quality red clover residue (*Trifolium pretense*; C:N=13) similarly, but there was greater difference in ability to decompose a low-quality wheat residue (*Triticum aestivum*; C:N=42), with higher decomposition in soils from more complex crop rotations (Fig. 1.2a). Using decomposition from two residues both limited by climate, but where one residue is not limited by biological activity and/or soil resources like potentially mineralizable N (e.g. high quality red clover), and one residue is limited by these factors (e.g. low-quality wheat residue) could potentially provide a climate-independent index of soil biological activity.

I propose using what I am calling the *Soil Decomposition Index* (SDI), which is the relative ability of a soil to decompose low-quality residue compared to its ability to decompose high-quality residue. It is calculated as the following:

$$SDI = \frac{Mass\ Loss\ of\ Low-Quality\ Residue}{Mass\ Loss\ of\ High-Quality\ Residue} = \frac{MLQ_{Day0} - MLQ_{DayX}}{MHQ_{Day0} - MHQ_{DayX}}$$

Where MLQ_{Day0} is the dry mass weight of low-quality residue before decomposition, MLQ_{DayX} is the dry mass weight of low-quality residue after *X* days of decomposition; and MHQ_{Day0} is the dry mass weight of high-quality residue before decomposition, MHQ_{DayX} is the dry mass weight of high-quality residue after the same X days of decomposition. While I recognize the terms 'high' and 'low' quality are somewhat arbitrary, ideally the high-quality residue would have a C:N less than 20 and the low-quality residue would have a C:N greater than 40, which is outside the C:N range where a shift in mineralization and immobilization occurs (Vigil and Kissel, 1991). But perhaps more important is the relative differences between the quality of the two residues.

Studies from agroecosystems that have used the green and rooibos teas (Table 1.1) provide a great resource to test this hypothesis. Many of these recent studies are comparing a conventional practice and a conservation practice or SHPP. I collected data from studies that have examined the effects of soil management on the decomposition of green and rooibos tea which are reported as having C:N of 12 and 43 respectively (Table 1.2). I searched GoogleScholar within studies that cited the original Keuskamp et al. (2013) for the keywords "agriculture soil decomposition OR agroecosystem OR soil management." I extracted mass loss data where available from Tables or from figures using Data Thief III (Tummers, 2006). I then used the data from the studies to calculate an *SDI* for the conventional and SHPP.

Overall, I found there to be a 19% positive effect of the SHPP on SDI. In a seven-year chronosequence study of no-tillage, both green and rooibos tea decomposition increased on average with length of time under no till management (Houben et al., 2018), but the no-tillage treatment increased the SDI with length of time in no till (except for year 7 which was highly variable) from 0.32 to 0.47 compared to tillage which had an SDI of 0.31. Cover crops are also considered a SHPP, and in one study the addition of a winter cover crop increased decomposition of rooibos tea, but actually slowed decomposition of green tea (Barel et al., 2019). This resulted in an overall 14% effect of the *SDI* from cover crops. Combined, these findings indicate that it might be possible to isolate soil health effects on decomposition from overarching climate effects by examining the ratio of decomposition of low quality residue to that of high quality residue (Figure 1.2b). With further research into validation and calibration of this index, *SDI* or a similar calculation could eventually be turned into a decomposition soil health index (Table 1.2).

1.3.3 Unique potential in agroecosystems

Soil health indicators to monitor improvement in management practices in agroecosystems are critical. Many indicators of soil health measure some aspect of soil biological activity because soil flora and fauna are typically the first component of soil to respond to change (Nielsen et al., 2002; Powlson et al., 1987). Many common agricultural practices alter the microbial community and its activity by changing the soil structure and/or the resources available to microorganisms. Since management history has a strong effect on decomposer organisms in agroecosystems, it creates a positive feedback loop that we will call the DFE (Fig. 1.1b). Agricultural management not only directly influences the decomposition pathway through land manager decisions like crop choice, planting date, residue removal, fertilization, and others that affect residue input quality, but it also directly affects the

decomposer community through some of the same management practices (including tillage). The effects of management can also be indirect especially through a long history of management that has depleted mineral soil organic matter and altered the biotic community, thereby feeding back to alter how new residue is processed and transformed into stable soil organic matter (Fig. 1.1b). These relationships, especially the DFE, make decomposition a good indicator to monitor changes in soil health that occur with management change.

There has already been some work that has successfully used decomposition of a standard substrate in this way. Winter cover crop legacy was shown to influence decomposition not only of native litter, but standardized foreign litter like tea bags and filter paper as well (Barel et al., 2019). Decomposition of tea bags was also found to be significantly related to length of time since conversion to no till, with higher rates of decomposition in plots that had received no till management the longest (Houben et al., 2018). These findings are encouraging and suggest that further research into decomposition as a soil health indicator for agroecosystems is warranted.

1.4. Decomposition of Household Items in Participatory Science and Education Outreach

In addition to the theoretical importance of decomposition in agroecosystems, decomposition of household items as indicators of soil health has the added advantage of being easy to use and inexpensive, which makes it more accessible to land managers than many alternative soil health measurements. This accessibility gives decomposition indicators the potential for widespread use both within the scientific community and with land managers. Combined with global organization efforts, decomposition indicators and citizen science could allow for the cultivation of a low cost/low effort, high-resolution dataset. An example of one such endeavor is the Global Tea Bag Index Network ("Teatime 4 Science," 2016) where citizens

can follow the outlined protocol and submit data they collect to a growing dataset online or through the Tea Bag Index smartphone app.

Participatory science also has the unique opportunity to help bridge the gap between sustainable agriculture in the abstract and actual practice. Developing sustainable agricultural systems is in part a social issue. It will require the cooperation of a number of key actors in addition to researchers including policymakers, consumers of agricultural products, and of course farmers. An effective way to spur change will be to engage as many of these stakeholders as possible in ways that are meaningful to them. Due to the complexity of interactions between agriculture and the environment, a one-size-fits-all approach is unlikely to be palatable. Farmers and other stakeholders are more likely to engage when questions asked and methods of measuring are specific to their unique ecological and social environment (Röling and Wagemakers, 1998). Offering them practical ways to take ownership of monitoring their specific operation or community for sustainability, and figuring out what works for their needs and goals might help cast a wider net.

In a similar vein, these citizen science techniques can serve as avenues for outreach and education. One such example is the #soilyourundies challenge that took off in 2015 (Coombs, 2015). Farmers were encouraged to bury a pair of cotton underwear for a period of time to qualitatively observe the decomposer activity in their soil (Fig. 1.3). With the help of social media, this challenge became an internet sensation, and farmers participated all over North America (Plaven, 2019). These accessible and easy to digest methods allow for inclusion and learning in a community where it is often not possible or practical to convene for such purposes.

1.5. Limitations to Using Decomposition of Household Items as Indicators of Soil Health

Like most indicators of soil health, the decomposition of common household substrates has some limitations. First, there are some issues with the availability and continuity of the indicators. While the household items commonly used are fairly ubiquitous, they are not always available everywhere. For example, Lipton's rooibos tea, used in the Keuskamp (2013) study and those following it, is unavailable in many local U.S. retail outlets and must be ordered from overseas. Lipton has also recently transitioned to new biodegradable tea bags, with highly variable mesh size, and is phasing out the more consistent nylon mesh used previously. While this is ultimately better for the environment, it likely affects the accuracy and precision of tea bags as soil health indicators, since changes in the weight of the biodegradable bag would confound tea decomposition data and heterogeneous mesh sizes will likely increase variability of decomposition rates, although this has not yet been tested.

Another potential barrier involved with decomposition of household items is the logistical difficulty within agricultural fields. The majority of microbial activity in soils happens near the surface (Nielsen et al., 2002), which necessitates a relatively shallow burial depth for the household items. There is usually some disturbance near the soil surface in all agricultural fields (e.g. tillage, sidedressed N fertilizer, etc.), so decomposition indicators can not be deployed until after these practices take place to prevent their destruction. This does not preclude use of decomposition as a soil health indicator, but might limit the time with which substrates are buried and for how long. Furthermore, management is also climate dependent, which can vary widely from year to year, also complicating interpretation. Finally, the variability with decomposition can be quite high (Barel et al., 2019; Lindley and Howard, 1988). This is probably partly due to the complex interactions of multiple factors that influence the

decomposition process, as well as the difficulty retrieving intact decomposition indicators that is occasionally experienced. While these obstacles warrant consideration, they are by no means insurmountable.

1.6. Future of Decomposition of Household Items as Indicators of Soil Health

As we continue to strive for better soil management, accessible soil health indicators, such as decomposition, will play an important role in generating interest as well as data with which to achieve our goals. In order to encourage adoption of this method we should aim to streamline the process in order to make it more straightforward. This might involve trials to determine the part of the season that gives the most helpful decomposition results, the optimum incubation time, and whether those parameters differ by region.

Adoption of decomposition as an indicator of soil health might also be encouraged and facilitated by leveraging technology. A growing number of smartphone applications are available to help farmers monitor various aspects of their operation, such as irrigation (Bartlett et al., 2015), and N use efficiency (Delgado et al., 2013). The Tea Bag Index app streamlines green and rooibos tea decomposition and observational soil data collection ("Teatime 4 Science," 2016), but at this point does not allow for interpretation or use of other substrates besides the Lipton green and rooibos teas. It might be possible to combine app technology with image algorithms that detect the amount of decomposition that has occurred based on an uploaded image, similar to algorithms that have been developed for other soil parameters like aggregate stability (Fajardo et al., 2016).

1.7 Conclusion

Soil health indicators are poised to become an important tool for citizens and scientists alike as we strive to improve our soil management practices. Decomposition of a standard

substrate shows great promise because there is evidence of theoretical underpinnings (Fig. 1.1b), linkages to soil health (Figs. 1.2 and 1.1b), its scientific robustness (Barel 2018; Houben 2018), as well as its accessibility due to low cost and ease of measurement. In this thesis I compare the decomposition of common household items to traditional indicators of soil health. My objectives are to validate decomposition as an indicator by relating it to traditional indicators, and to compare the signal-to-noise ratios of both types.

1.8. Figures

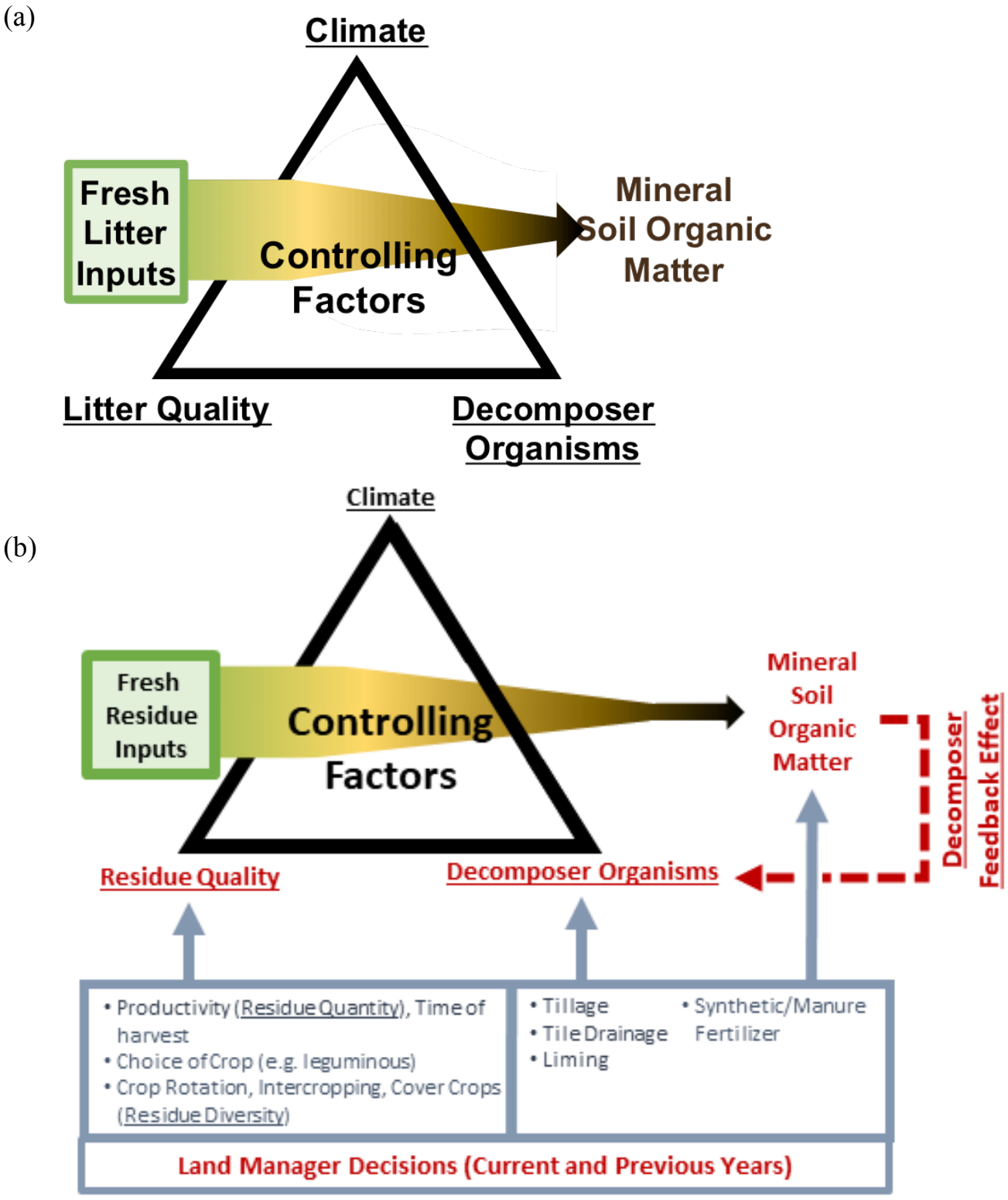
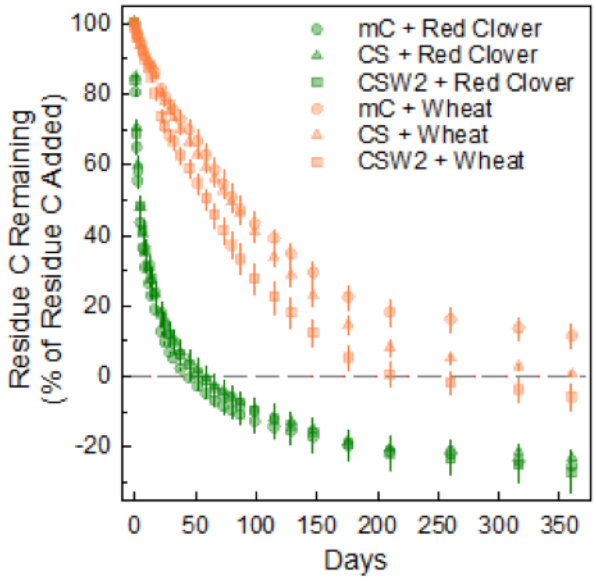


Figure 1.1 Controlling factors on decomposition of litter and transformation to mineral soil organic matter. (a) Classic model of controlling factors, adapted from Bradford et al., 2016; and Swift et al., 1979. (b) Modified model factoring in land manager decisions.

(a)



(b)

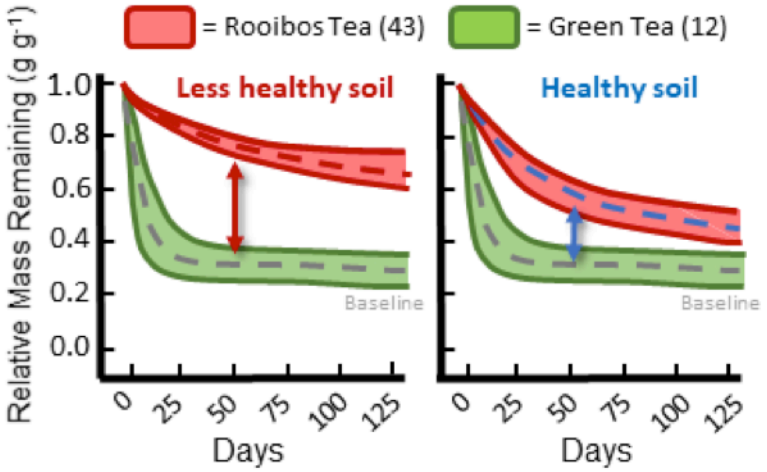


Figure 1.2. Potential for decomposition of dual household items to measure soil health. (a) Residue (red clover & wheat, C:N of 13 & 42) decomposition when added to three soils under 12-year crop rotations – monoculture maize (mC), maize-soybean rotation (CS) and maize-soy-wheat plus two red clover and rye cover crops (CSW2) calculated from McDaniel et al., 2014. (b) Rooibos and green tea data adapted from Keuskamp et al. 2013 in a 'less healthy' and 'healthy' soil (hypothetical data). Dashed lines are mean values; ranges are decomposition at 15 °C and 25 °C.

Figure 1.3. A demonstration of the 'Soil Your Undies' challenge in which farmers were encouraged to bury cotton underwear in their soil as a qualitative measurement of biological activity. Clockwise from the top the treatments represented are perennial pasture, no till soybeans with a cereal rye cover crop, no till soybeans, conventional corn, and alfalfa. Photo and demonstration by Neil Sass of the Waverly, IA Soil Survey Office.

1.9. Tables

Table 1.1. Summary of several representative decomposition studies using manufactured items.

Original Study	Indicator(s)	Number of Citations	Responses measured	Purposes
Deacon, 1985	Filter paper (*Gossypium hirsutum*)	41 (49)†	% Mass loss, Decomposition rate	Compare decomposition by various fungi alone and in concert; examine relationships between cellulose decomposition and plant growth/soil properties; examine controls on decomposition over several sites; examine effects of previous crop on decomposition
Latter and Howson, 1977b	Cotton (*Gossypium hirsutum*)	57 (77)†	Tensile strength, Decomposition rate, % mass loss	Examine differences in decomposition between forest thinning treatments; determine effects of temperature and moisture changes on ecosystem processes; compare methods of measuring invertebrate contributions to decomposition;
Sinsabaugh et al., 1992	Birch sticks (*Betula spp.*)	24 (160)†	% Mass loss, Decomposition rate	Compare decomposition to extracellular enzyme activity; observe decomposition in floodplain communities; nutrient cycling during decomposition
Keuskamp et al., 2013	Green tea (*Camellia sinensis*) Rooibos tea (*Aspalathus linearis*)	117 (136)†	Relative mass remaining, Decomposition rate (k), stabilization factor (S), % Mass loss, % Mass remaining	Detect differences between ecosystems; compare decomposition of standard and local litter, observe effects of elevation on both; examine the effect of previous crop on decomposition; determine effects of no till management on decomposition; determine effects of different cover crops on decomposition and nutrient release
This study	Green tea (*Camellia sinensis*) Rooibos tea (*Aspalathus linearis*) Cotton (*Gossypium hirsutum*) Birch sticks (*Betula spp.*)		% Mass loss	Compare decomposition to traditional soil health indicators and examine the ability of both to detect treatment differences

† Parentheses indicate total citations, and the preceding number indicates citations that used the same method.

Table 1.2. Examples of Soil Decomposition Indexes (SDI) calculated from crop residues and green and rooibos tea decomposition in several recent papers.

Paper	Conventional Management or Control Treatment	Soil Health Promoting Practice (SHPP) Treatment	Control Mean SDI	SHPP Mean SDI	Change in SDI from SHPP (%)	SHPP Range SDI where applicable	Length of Incubation
McDaniel et al, 2014†	Monoculture corn	Corn-Soy-Wheat + 2 cover crops	0.67	0.85	26.90%		360 days
Barel et al, 2018	Fallow after oat	Cover crop after oat	0.43	0.48	11.60%	0.43 - 0.54	63-65 days
Barel et al, 2018	Fallow after endive	Cover crop after endive	0.43	0.5	16.30%	0.45 - 0.56	63-65 days
Houben et al, 2018	Conventional Tillage	No Till (1-7 years)	0.31	0.37	19.35%	0.29 - 0.47	30 days

†Red clover and wheat residue were used in this paper (McDaniel et al., 2014).

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CHAPTER 2. DECOMPOSING HOUSEHOLD ITEMS COMPARED TO TRADITIONAL SOIL BIOLOGICAL MEASURES IN RESPONSE TO SOIL HEALTH PROMOTING PRACTICES

2.1 Abstract

As the soil health movement continues to garner attention, it is important to make measuring soil health more accessible – usually by decreasing cost and/or making measurements easier – in order to encourage soil health promoting practices (SHPPs). Soil health emphasizes the biological component of soil, so traditional indicators of soil health usually focus on microbial biomass, their activity, and/or the nutrient pool available to microorganisms and plants. These measurements are useful, but they can be highly variable in time and space, and they often require equipment and expertise that is beyond the average land manager. Decomposition is a critical soil process that is integral, and related to, many soil ecosystem services we care about for soil health.

Here I compared the extent of decomposition of common household items: green and rooibos tea, cotton underwear, and birch craft sticks (referred to as decomposition indicators in this thesis) to traditional soil health indicators: microbial biomass carbon and nitrogen, permanganate oxidizable carbon, and potentially mineralizable carbon and nitrogen. My first objective was to validate the decomposition of these household items as indicators of soil health by correlating extent of decomposition to the traditional biological indicators of soil health, and arguably the ultimate soil health indicator, maize yield. This objective was carried out on various soil and management types around the state of Iowa, but only considered conventional management practices. The second objective was to evaluate the ability of traditional and decomposition soil health indicators to detect differences between SHPPs and a control treatment of conventional Midwest agriculture practices across nine long-term experiments. These

experiments contrasted conventional management practices with biochar addition (8 t ha^{-1}), use of a winter cover crop (cereal rye – *Secale cereale*), diversified crop rotations, adding nitrogen fertilizer, no-tillage, using a perennial crop instead of an annual (*Miscanthus giganteous*), the addition of residue, and restored prairie.

Surprisingly, the traditional and decomposition indicators were not often related to one another, but when they were it was negative relationship. Decomposition of household items, specifically 4 day incubations of green and rooibos tea, better correlated with maize yield than traditional indicators ($p<0.001$ compared to $p=0.005$ or greater). When comparing ability to detect a 'signal-in-the-noise', or differences in management practices, the decomposition indicators, specifically early stage rooibos tea and bleached cotton outperformed many of the traditional indicators of soil health. Rooibos tea at 4 days detected treatment differences in 63%, of SHPPs and both cotton and rooibos tea at 7 days detected differences in 38% of SHPPs, while most traditional indicators only detected differences in 13-25% of SHPPs with the exception of spring microbial biomass nitrogen, which detected differences in 50% of SHPPs. Based on these findings, I recommend using a 4-day incubation of rooibos tea as an indicator of soil health. Decomposition of common household items was not only more inexpensive and easy to measure, but also at least as sensitive to SHPPs (if not more) as traditional soil health indicators. This means that decomposing household items shows promise as an easily accessible way for citizen scientists to measure changes in soil health in their fields.

2.2 Introduction

Modern cultivation practices have depleted soil organic matter (SOM) by as much as 10-59% (Guo and Gifford, 2002); and interventions are needed in order to regenerate SOM and restore the soil ecosystem services (SES) lost with this SOM if we are to sustainably feed 9-10 billion people by 2050. However, tracking soil progress after a shift in management practices can be difficult. Soil health has emerged as a framework for monitoring progress on restoring SOM, and in particular, the SES that are regulated by soil biota like nutrient supplying power. While SOM content changes slowly and is relatively insensitive to management, especially in soils that are already high in SOM concentration – such as soils in Midwestern U.S. where concentrations can range from 2 to 8%, other processes that link SOM and soil health respond more quickly and can be used as indicators.

As we move into an era characterized by a changing climate and a growing global population, it is imperative that we make soil health a priority when determining how to manage our land. Soil health has implications for important SES as well as for production. Soil health impacts air and water quality, biodiversity, and nutrient cycling (Barrios, 2007; Doran, 2002), as well as crop yield and sustainability (Drinkwater et al., 1998; Romig et al., 1995). An important part of the effort to improve soil health is finding a way to make it more accessible, so that land managers can assess their progress after a change in soil management (Doran, 2002).

Soil health is currently assessed using various tests, which each have their own indicators. Ideally, a soil health indicator should meet these following criteria (Doran and Zeiss, 2000; Morrow et al., 2016): i) be scientifically robust and based on direct or indirect linkages to SES, ii) have repeatable results and an acceptable range of variability (CV<15%; Morrow et al. 2016), iii) be sensitive to management changes so that progress can be tracked, iv) be

comprehensible and easy to use, v) be inexpensive and accessible to encourage adoption by land managers, vi) and also offer insight into how to remedy shortcomings in soil health so that management decisions can be adjusted accordingly. Soil health indicators often focus on measuring soil biota and their activity, because they are directly involved in cycling nutrients and sequestering carbon (C) in soils (Barrios, 2007; Falkowski et al., 2008; Kibblewhite et al., 2008), and are often found to be highly sensitive to management practices (Nielsen et al., 2002).

Some common traditional indicators of soil biology or activity are microbial biomass C and N (MBC, MBN; Vance et al., 1987; Brookes et al., 1985), potentially mineralizable C and N in short- or long-term incubations (PMC, PMN; modified from Franzluebbers, 2018; McDaniel and Grandy, 2016), and other measures of active SOM like permanganate oxidizable C (POXC; Weil 2002). These measures are the 'gold standards' for soil biomass and activity or resources available to soil microorganisms (Table 2.1). There is a plethora of evidence that they are highly sensitive to management practices such as: reduced tillage (Houben et al., 2018; Wardle et al., 1999), crop rotations (McDaniel & Grandy. 2016), manure addition (Ringelberg et al., 2002), cover crops (Barel et al., 2019), and other management practices that generally increase soil health. However, these measures are also quite variable across space (Cambardella et al., 1994) and time (Debosz et al., 1999); thus making effects of management difficult to detect. In addition, detracting from wider adoption of these measurements is their high cost and low-throughput – violating at least one criterion mentioned above. The variability and high cost of these tests might deter some land managers from regularly tracking their soil health.

An alternative to these traditional indicators of soil health and biological activity is the decomposition of a common substrate. Decomposition, a critical process in all soils, is driven by a diverse suite of soil biota and is directly linked to key soil SES – mostly nutrient cycling and

organic matter accumulation (Doran and Zeiss, 2000; Swift et al., 1979; Wickings et al., 2012), and it responds to management changes like residue input, cover crops, and crop rotation (Barel et al., 2019; McDaniel et al., 2014), indicating that decomposition of common substrates has the potential to be a sound measure of soil health that will be able to detect management differences.

Soil ecologists have decomposed manufactured or common substrates to infer soil biological activity across a wide variety of ecosystems with several different substrates for many decades. This approach is attractive for its simplicity, its use of a standardized substrate, and because it is an integrated measure over time rather than the 'snapshot' approach of collecting one soil sample over a growing season. One of the first popular substrates was cotton via the cotton strip assay (Latter and Howson, 1977a; Springett, 1971). Cotton decomposition has commonly been measured as tensile strength loss, but in some cases mass loss or decomposition rate is used (French, 1988; Howson, 1988; Nys and Howson, 1988). Wood from different tree species (beech (*Fagus sylvatica*), tulip tree (*Liriodendron tulipifera*), birch (*Betula papyfera*), lodgepole pine (*Pinus contorta*)) has been used to study the effects of macrofauna and enzyme function on nutrient cycling in forest ecosystems (A'Bear et al., 2014; Ausmus, 2013; Sinsabaugh et al., 1992; Spears et al., 2003), where fungi are important decomposers (Rayner and Boddy, 1988; Ulyshen, 2016). Most recently, Keuskamp et al. (2013) decomposed two types of tea leaves in nylon mesh bags in a variety of ecosystems. They showed that mass loss of the two teas (differing in C:N – 12 vs 43) at one time point could be used as an index of decomposition. This method is particularly appealing because the tea is pre-packed in a litterbag, which is the most common method for measuring decomposition (Bärlocher, 2005; Meentemeyer, 1978; Wieder and Lang, 1982). For its simplicity, this approach has garnered a

lot of attention with both professional and citizen scientists alike (Djukic et al., 2018; Lehtinen, 2017; Poeplau et al., 2018).

Like the traditional indicators of soil health, decomposition can be highly sensitive to management practices, (Baumann et al., 2009; Powlson et al., 1987). The benefit of decomposing common household items as indicators of soil health compared to traditional methods is that these substrates are inexpensive and readily available in local retail outlets. However, convenience and cost should not take the place of scientific rigor, and the use of decomposition as a soil health indicator needs to be validated. An inexpensive and ubiquitous common substrate will allow for broad measurements across climates, soil types, and various management practices. My objectives were two-fold: 1) evaluate decomposition of common substrates as proxies for traditional soil health indicators through correlation, and 2) compare decomposition and traditional soil health indicators in their ability to detect differences in SHPPs under similar climate and soil types in Iowa, United States, a key region for maize (*Zea mays*) and soybean (*Glycine max)* production. I decomposed four common substrates (Table 2.2) – green tea leaves (*Camellia sinensis*), rooibos tea leaves (*Aspalathus linearis*), bleached and processed cotton (*Gossypium hirsutum*), and processed birch (*Betula spp*.) wood – to evaluate whether eight SHPPs affect the extent of their decomposition (i.e. mass loss) and compared decomposition results to traditional soil health indicators taken at two different times during the growing season. The SHPPs included: biochar addition (8 t ha^{-1}), use of a winter cover crop (cereal rye –*Secale cereale*), diversified (4-year) crop rotations, adding synthetic nitrogen fertilizer, no-tillage, using a perennial crop instead of an annual (e.g. *Miscanthus giganteous* instead of maize), adding residue, and reestablishing prairie on cropland.

2.3. Materials & Methods

2.3.1. Site description and experimental layout

This study focused primarily on nine Iowa State University agroecosystem research experiments (Table 2.3) in Iowa, U.S. Six of these sites are located at an Iowa State University research farm near Boone, Iowa (42°01'N, 93°46'W; Fig. S2.1), and the Comparison of Biofuel Systems was located site 14 km south. The Neely-Kinyon farm site was located in Greenfield, Iowa and the Agriculture Drainage and Water Quality Research and Demonstration site was located in Gilmore City, Iowa. The soils at all sites are Mollisols, with Nicollet loam, Clarion loam, and Webster clay loam representing the three most common soil series at all sites (Table S2.1). Most (7/9) of the long-term experiments contained a maize (*Zea mays*)-soybean (*Glycine max*.) rotation with fertilizer N added before maize and disc tillage – which is the 'business as usual' crop rotation and management practice used in the area and treated as the a control treatment (with some exceptions – Table 2.3). SHPPs and treatments ranged from 2 to 17 years in place (Table 2.4). All experiments were randomized complete block designs, with a range of 3 to 5 replicates for each treatment. All sites with maize were planted between April and May and harvested in October in 2018.

An additional nine site-years were included when checking for correlations between traditional soil health indicators and tea bag decomposition. This data was from eight commercial farms participating in cover crop strip trials throughout Iowa in 2017, and one long-term cover crop experiment that was also measured in 2018. These sites were located in central, southwest and southeast Iowa. They were primarily Mollisols with the exception of a site in Jamaica, IA that was an Alfisol. These sites contained a maize (*Zea mays*)-soybean (*Glycine max*.) rotation with fertilizer and in some cases manure N added before maize.

2.3.2. Traditional soil health indicators

Soil sampling occurred twice for each site, once 1-2 months after planting (mid-June-late July 2018) and once close to harvest (mid-October-early November 2018). Soil sampling locations were co-located within 2 m of the buried household items. Each composite sample consisted of 10 cores from 0-15 cm depth using a soil probe (2 cm diameter). After collection, the soil samples were stored on ice until transported back to the laboratory, where they were refrigerated at 4°C until being processed and analyzed.

Microbial biomass C and N (MBC and MBN) were measured using the chloroform fumigation-extraction method (Vance et al., 1987; Brookes et al., 1985). Fresh 2 mm sieved soil (5g) was fumigated in 30 mL ethanol-free chloroform for 24 hours in the absence of light at 25 °C in a vacuum-sealed desiccator jar (Horwath and Paul, 1994). Another 5g of corresponding fresh 2 mm sieved soil was not fumigated, but left at 25°C without light for 24 hours. Fumigated and non-fumigated samples were extracted with 0.5M potassium sulfate, shaken for 1 hour at 150 rpm on a reciprocal shaker, centrifuged at 2000 rpm for 2 min, and filtered through an 11 μm Whatman no. 1 cellulose filter paper into plastic scintillation vials, in which the extract was stored and frozen until analysis. Extracts were analyzed for non-purgeable organic C and total N via combustion catalytic oxidation (Shimadzu TOC-L analyzer, Shimadzu Corporation, Columbia, Maryland, USA) after adding phosphoric acid to remove carbonates. Microbial biomass C and N were calculated using the difference in extractable organic C (or total dissolved N) between the fumigated and non-fumigated samples. The difference in extractable organic C and total dissolved N were divided by a extraction efficiency factor of 0.45 and 0.54, respectively, to find microbial biomass C (Joergensen, 1996) and N (Brookes et al., 1985).

Permanganate oxidizable carbon was measured according to Weil et al., 2003. Air-dried soil was shaken with a potassium permanganate reagent for 2 minutes on a reciprocal shaker at 120 rpm. After settling for 10 minutes, supernatant was diluted by a factor of 100 with deionized water and run on a Biotek Synergy HTX multi-mode reader to determine absorbance at 550 nm. Oxidizable C was calculated by relating the absorbance to the amount of reagent reduced.

Potentially mineralizable carbon was calculated by measuring carbon dioxide (CO_2) produced during a 14-d incubation. Five 5 g of air-dried soil was brought to 50% water holding capacity, calculated by measuring the water mass retained in the soil 6 hours after submerging, in 50 ml conical centrifuge test tubes (modified from McDaniel and Grandy, 2016). During the incubation, CO_2 concentration was measured in test tube headspace on a LI-830 CO_2 gas analyzer (LI-COR, Lincoln, NE). CO_2 production was measured as the difference between a T_1 measurement after closed incubation and T_0 measurement, right after flushing with ambient air. T_1 measurements ranged from 8-h to 5-d after flushing. Potentially mineralizable nitrogen was measured on this same soil by subtracting total inorganic N (ammonium plus nitrate) extracted from the soil at the end of the 14-d incubation from the total inorganic N extracted prior to incubation.

2.3.3. Decomposition of household substrates

I chose to decompose commercially available items so that producers would have easy access to them (Table 2.2). All household items used in this study were buried after planting maize and in most cases after sidedress nitrogen was applied – between late May- early July 2017 and mid-June-late July 2018. However, items were retrieved at various times across the growing season depending on the material and how fast it decomposed.

I used two types of commercially-available tea bags as decomposition substrates in this experiment: a green tea and a rooibos tea, both produced by Lipton (Unilever, London, UK;Table 2.2). The tea comes packaged in tetrahedron-shaped nylon mesh bags (mesh size 0.25 mm), with an attached nylon string, and a paper label. I reinforced the tea bags by tying a fishing line through the bag and attaching the fishing line to the label with electrical tape. The tea was dried at 40 °C for 24 h and weighed before deploying for burial. I buried six green and six rooibos tea bags in each plot, eight cm deep, alternating green and rooibos bags in two rows 10 cm from each crop row. Both green and rooibos teas were retrieved 4, 7, 14, 30, 68, and 130 days after burial. Upon recovery, the tea bags were stored on ice until they were transported back to the laboratory, where they were refrigerated at 4°C until being processed. The tea bags were oven dried at 40°C for 4 days and weighed again. The contents of each tea bag were then burned at 530°C for 8 hours and the remains were considered mineral soil contamination and subtracted from the final tea weight for ash-free dry mass.

Bleached, processed cotton was purchased as 100% cotton mens' brief underwear from Fruit of the Loom Inc. After taking an initial weight, one piece of cotton was buried in each 2018 plot in a 7.6 cm deep trench. The elastic waistband was left above the soil as a marker. After 35 days the underwear were retrieved and stored on ice until transported back to the laboratory, where they were refrigerated at 4°C until being processed. They were washed to remove soil and debris, and then dried at 60°C for 24 hours and a final weight was taken. Mass of the elastic bands for waist and legs were subtracted from the total.

Several studies have used birch (*Betula spp*.) wood craft sticks for fungal decomposition (Hobbie, 2005; Sinsabaugh et al., 1992). Similarly, I used a 15 cm craft stick made of birch wood from Horizon Group USA. A small hole was drilled 1 cm from the top end of the stick through

which fishing line attached to an electrical tape marker was tied. An initial weight was taken before burying each stick. One stick was buried vertically in each 2018 plot, using a soil knife to create a crevasse into which the stick was placed with the top end of the stick 1.3 cm below the soil surface. They were left in the ground for approximately 130 d. After retrieval, the sticks were stored on ice until transported back to the laboratory, where they were refrigerated at 4 °C until being processed. The sticks were washed to remove soil and debris, and then dried at 60 °C for 24 h before a final weight was taken. Stick mass loss was calculated by comparing a 2.5 cm segment of processed post-burial stick to an estimate of the pre-burial 2.5 cm segment weight. This estimate was calculated based on a 20-stick average ratio of 2.5 cm to total stick weight.

2.3.4. Yield and ancillary soil data

Yield was collected for each plot typically with a 4-row plot combine from the center rows of the plot, corrected to 15.5% moisture and extrapolated to Megagrams per hectare. No yield data was collected at the Boyd farm site for the 2018 growing season, so yield from 2017 was substituted, but not used for correlations since the physical plots were different in 2017.

Soil volumetric water content (0-7 cm depth) was measured using an HH2 Moisture Meter (Delta-T Devices Ltd., Houston, TX, USA), and soil temperature (0-10 cm depth) was measured using a Digital Pocket Thermometer (W.W. Grainger Inc., Lake Forest, IL). Three measurements per plot were co-located within 2 m of the buried household items each for volumetric water content and temperature. Bulk density was measured using 250 cm^3 steel rings at 2 depths: 0-5 cm and 5-10 cm, with three replicates per depth per plot. Retrieved soil was oven dried at 105 °C for 24 hours, weighed and divided by the ring volume. Gravimetric moisture content was measured on 2 mm sieved soil by comparing fresh weight to final weight after oven drying at 105 °C for 24 hours (Gardner, 1986).

Total soil carbon and nitrogen and pH were measured on air-dried soil. Ground soil was analyzed for total carbon and nitrogen using an Elementar vario MACRO (Elementar Americas Inc., Ronkonkoma, New York, USA). Soils were ball-milled, oven dried at 105 °C for 24 hours, and combined with at least equal parts of tungsten oxide catalyst. Soil pH was measured with HQ430D Laboratory Single Input pH glass Electrode probe. 10 g 2mm sieved air-dried soil was mixed with 20 mL deionized water and stirred for 3 minutes to create a slurry prior to reading. Adapted from Thomas, 1986.

2.3.5. Data handling and statistical analyses

After checking for outliers by using three standard deviations from the mean as a threshold, I tested whether decomposition indicator results correlated with traditional results, by fitting linear models to each pair of decomposition and traditional indicators (R Core Team, 2018). Any regression with a p-value<0.1 was considered at least weakly correlated. The same was performed for combinations of yield and all indicators.

For both traditional and decomposition indicators, I investigated the power to detect differences between control and SHPP treatments. I modeled the estimated means for control and SHPP plots and used an ANOVA F-test to calculate a p-value for each indicator/SHPP combination. P-values less than 0.05 were considered successful treatment detections. The power of an indicator is mathematically related to the p-value, where more powerful indicators generate smaller p-values for the same sample size and variance. For each SHPP, I ranked p-values to determine which indicators had the most power to detect differences between control and experimental levels of the SHPP.

To calculate estimated means for control and SHPP plots for each indicator, I created post-hoc blocks by subsetting the data by site and SHPP. After removing missing values, sample

sizes for both decomposition indicators and traditional indicators ranged from $n = 4$ control plots, $n = 4$ SHPP plots in the restored prairie treatment, to $n = 16$ control plots, $n = 16$ SHPP plots in the cover crop and no tillage treatments (average $n = 10$ control and $n = 10$ SHPP plots over all SHPPs). All models were of the general form:

$$indicator\ value \sim block + treatment\ (control\ or\ SHPP)$$

where "indicator value" was the percent mass loss for decomposition tests and raw measurements of N, C, etc. per kilogram of dry soil for traditional indicators. Values for traditional indicators over the entire dataset were normally distributed, so I modeled traditional indicators with linear regression models using ordinary least squares in R (R Core Team, 2018). For decomposition indicators with responses on the percentage scale, I ran beta regression models using the betareg package in R (Cribari-Neto and Zeileis, 2010). I calculated estimated means, ANOVA tables, and p-values in the emmeans package in R (Lenth, 2019).

I was interested in comparing the relative power of different indicators to resolve differences between control and SHPP conditions for each treatment, so I combined both traditional and decomposition indicators and ranked p-values for each SHPP. To determine if the ranking of p-values was more ordered than would be expected by chance, I computed and tested the coefficient of concordance among several judges (SHPPs) through a permutation test using the kendall.global function in the vegan package in R (Oksanen et al., 2019)

In order to better understand how each indicator responded to control versus SHPP conditions, I compared signal and noise for each indicator in each combination of site and SHPP. I plotted the mean signal, or percent difference due to SHPP ((SHPP estimated mean – control estimated mean)/control estimated mean*100), along the x-axis, and the average noise, or coefficient of variation (σ/μ), between control and SHPP treatments along the y-axis.

2.4. Results

2.4.1. Weather and soil microclimate

In central Iowa, where seven of the nine core sites were located, mean annual temperature (MAT) and precipitation (MAP) are 8.7 °C and 970 mm respectively. Average temperature for this area in both 2017 and 2018 was 8.0 °C, slightly cooler than average. Central Iowa received 860 mm total precipitation in 2017, and 1230 mm in 2018. The higher than average precipitation in 2018 affected planting. I observed very little effect of SHPPs on soil temperature and moisture on a plot scale throughout the growing seasons (Figs. S2.2 and S2.3). The largest treatment difference was found between perennial crop *Miscanthus giganteus* and conventional maize. Soil temperature 11 cm under *Miscanthus giganteus* was more stable throughout the season, with 18% cooler temperatures from July-September, and 53% warmer temperatures in November (Fig. S2.2). Greater variation was observed in moisture response to treatment, with prairie showing the most substantial difference in moisture at a depth of 6 cm from its conventional corn control, with an average 11% increase in moisture compared to conventional controls. On the other hand, no-till and diversified rotation treatments were both drier than their conventional controls (2% and 4% respectively), especially toward the end of the season (Figure S2.3).

2.4.2. Relationships between decomposition, traditional soil health indicators, and yield

Correlating decomposition with both yield and traditional soil health indicators is one way to validate that decomposition is indeed measuring soil biological activity or soil health. For this objective, I used data from 2017 and 2018 but only the control treatment, i.e. conventional management practices of each SHPP treatment pair, in order to prevent confounding treatment effects. I predicted that decomposition of household items would positively relate to yield and traditional soil health indicators.

2.4.2.1. Decomposition and yield correlations

For decomposition correlations with yield I used maize only, due to the limited number of soybean fields available (Table 2.4). These data also included commercial farms (Table S2.2) and long-term university experiments (Table 2.4), with ranges in management and fertilizer N application rates ranging from 0 to 170 kg N/ha. Maize yield ranged from 4.2-18.6 Mg/ha with a mean of 12.7 (Table 2.5). There was not a significant N effect on yield. The tillage site had the lowest mean yield at 7.8 Mg/ha, and the biochar site had the highest mean yield at 15.7 Mg/ha.

It can be argued that crop growth or yield is the ultimate soil health variable that integrates physical, chemical, and biological soil health. I compared maize yield where available to both traditional and decomposition indicators to determine if any relationship between the two existed, as this is an important parameter for some land managers. Yield correlated strongly with PMN from the 2017 experiments (spring $p=0.007$, $R=0.68$; autumn $p=0.005$, $R=0.73$), but did not correlate with any other traditional soil health indicators. Yield was positively correlated with green and rooibos tea decomposition at 4 and 130 days (p ranged from $<0.001 – 0.075$; R ranged from 0.29 – 0.60 (Table 2.6, Fig. S2.4).

2.4.2.2. Decomposition and traditional soil health indicator correlations

Traditional soil health indicators were measured in both spring and autumn in order to 'book end' the decomposition measurements. I have soil measurements at initial burial of household items (0 d) that probably better relates to early stages of decomposition, and soil measurements at the final decomposition measurement (130 d). The range and mean for each traditional indicator across both spring and autumn samples is: MBC= 97-720, μ=308 mg C/kg dry soil; MBN=2-96, μ =39 mg N/kg dry soil; POXC=115-933, μ =543 mg/kg dry soil; and

PMC=7-175, μ=79 μg CO_2-C/g dry soil (Table 2.5). Only PMN values from 2017 were used, and those ranged from below detection to 175 with a mean of 87 mg/kg dry soil.

Of the 56 pairs of traditional and decomposition indicators that I examined, 20 yielded at least a weak correlation ($p<0.1$) (Table 2.7, Figs. S2.5 and S2.6). Of the 20 total instances of correlation only four were positive, and the rest were negative. In the spring I primarily saw negative relationships between the two teas and PMC (p-value = 0.003 – 0.087; R ranged from -0.34 to -0.21). There was also a positive relationship between MBC and green tea decomposition at 130 d, albeit marginally significant ($p=0.073$, $R=0.22$), and a positive relationship between rooibos tea decomposition at 130 days and PMN ($p=0.049$, $R= 0.35$), as well as a slightly negative relationship between rooibos tea decomposition at 4 days and PMN ($p=0.063$, $R= -0.31$, Table 2.7, Fig. S2.6). In the fall I saw negative relationships between MBC and MBN and the two teas at 4 days, rooibos tea at 130 days, and cotton (p-values = <0.001-0.078; R ranged from -0.41 to -0.23). PMC negatively correlated with both teas, while PMN negatively correlated with rooibos tea decomposition at 4 days (p = <0.001-0.088, R ranged from -0.38 to -0.29). POXC was the only indicator to positively correlate with any decomposition indicators in autumn (p ranged from 0.047-0.070, R ranged from 0.22-0.25, Table 2.7, Fig S2.6).

2.4.3. Treatment effects on decomposition and traditional soil health indicators, and comparisons of signal-to-noise

In order to compare the ability of each decomposition and traditional soil health indicator to resolve treatment differences among several SHPPs, I compared the effect size (signal) and variation (noise) for each experimental and control treatment mean pair. First, I look at overall indicator response to SHPP treatment by examining the magnitude and direction of difference

due to treatment (Figs. 2.1 and 2.2). Second, the effect size and variation are compared between decomposition and traditional soil health indicators (Figs. 2.3, 2.4, and 2.5).

2.4.3.1. Magnitude and direction of treatment effects on decomposition and traditional soil health indicators

Generally, very few significant differences in traditional soil health indicators across all SHPPs were observed (Table 2.8, Fig. 2.1). Spring sampling appeared to show more frequent SHPP treatment effects, with greater magnitude of difference between treatments than the autumn sampling in 6/8 SHPPs, and 51% greater magnitude on average. Restored prairie showed the greatest number of significant positive effects on traditional soil health indicators (4 of 8) with median differences ranging from 35-224%. Interestingly, adding more crop residue seemed to decrease MBN, POXC, and PMC by 29, 16, and 47% respectively.

Similar to traditional soil health indicators there were many times that decomposition did not detect any treatment differences among our eight SHPPs. However, perennial cropping and no-tillage had the most consistent and strongest effect on decomposition (Table 2.8, Fig. 2.2). Most SHPPs increased decomposition compared to their conventional counterpart, with the exception of perennial cropping which was consistently slowing decomposition of tea leaves by 3-40% (except for rooibos tea at 7-d), but increased decomposition of cotton by 86%. This negative effect seemed to diminish with time. Interestingly for both teas, especially the rooibos tea, the initial stages of decomposition were generally much more sensitive to management practices than later stages of decomposition – specifically in cover crops, restored prairie, and no-tillage. Rooibos tea at 4-d was the most sensitive to SHPPs out of any indicator, whether traditional or decomposition.

2.4.3.2. Strength of treatment effects and variability in decomposition vs. traditional soil health indicators (signal-to-noise)

Ideally, an effective soil health indicator that has the ability to detect differences between management practices should have low variability. I compared variability around treatment means (Figs. 2.1 and 2.2) for both decomposition and traditional soil health indicators using raw coefficients of variation within means (CV, Fig. 2.3). Yield had by far the lowest and most narrow distribution of CVs, with a median CV of 6%. The traditional soil health indicators had median CVs between 14 and 31%, and each indicator showed wide range of CVs across management practices.

Management effects on decomposition of household items was also highly variable (Fig. 2.3). Green and rooibos tea showed the lowest CVs out of decomposition soil health indicators, with medians of 4 and 13% respectively. Bleached cotton and birch craft sticks, however, were much more variable across SHPPs, and median CVs of 55 and 28%, respectively.

A soil health indicator should be sensitive to management practices – in other words it must have a high signal (or treatment effect) and low noise (random variability). I examined this signal-to-noise ratio using two methods. First, I simply plotted the percent difference due to SHPP (i.e. the signal) to the coefficient of variation (i.e. the noise) for each site/SHPP combination (Fig. 2.4). Second, I used the p-value from the ANOVA on treatment effects and estimated means comparison as a measure of signal-to-noise (Fig. 2.5). Accordingly, I classified soil health indicators as superior if they showed either greater signal compared to noise or had lower p-values. Using the median signal and noise as guides (Fig. 2.4), I found that out of the 41 indicators that exhibited greater than median signal and less than median noise, 32 were decomposition indicators. The traditional soil health measures that were more sensitive to SHPPs

were MBC and PMC. Sixty-one percent of the high signal, low noise decomposition indicators were early stages of tea decomposition (4-14 d), with rooibos tea accounting for 51% of the total above median indicators. Across all SHPPs 17% of the traditional indicators fell below the p-value of 0.05 (Fig. 2.5). In contrast, 22% of decomposition indicators fell below this same p-value. In order to qualitatively determine which indicators were more frequently better at detecting differences across all SHPPs I ranked them based on relative p-value for each SHPP, and overall based on the sums of their rankings (Table 2.9). Spring PMC and MBN had the most consistently low p-values for traditional indicators, and early stage rooibos tea (4 d) and cotton decomposition had the most consistently low p-values for decomposition indicators. The order of the p-value rankings was not significant, however. The coefficient of concordance permutation test yielded a p-value of 0.183, providing no statistical evidence that p-value rankings were more ordered than would be expected by chance.

2.5. Discussion

Monitoring soil health is essential to moving toward a more regenerative and sustainable agriculture. One way to enhance soil health monitoring is to use methods that are easily accessible, require little labor, and are inexpensive. Making this monitoring more accessible to land managers has a two-fold impact on soil health. First, it allows land managers to become engaged in the monitoring process via participatory or citizen science by doing things like on-farm strip trials or collecting soil health data, and this engagement has the potential to lead to general increase in public interest and awareness of SHPPs (Cooper et al., 2007). Second, land managers can contribute to large data sets when methods of monitoring soil health are easy and inexpensive.

Decomposition of household items has been used mostly as an extension demonstration tool (see #SoilYourUndies Houghton, 2018), but recent studies have shown that decomposition of these household items is sensitive to SHPPs, thus indicating their potential for use as an indicator of soil health (Barel et al., 2019; Houben et al., 2018) . My overarching goal was to compare decomposition of household items to traditional indicators of soil health that are more-or-less out of reach of the average land manager. I compared these two types of soil health indicators in their ability to predict plant growth or yield – a key SES to producers, and ability to detect differences in known SHPPs by observing signal-to-noise ratio. Overall, I found decomposition was somewhat related to soil microbial C and N processes, and sometimes in unexpected ways, but it far outperformed traditional soil health measures in predicting maize yield (Table 2.6). Variability of tea decomposition was comparable to traditional soil health measures, but bleached cotton and birch wood were much more variable. The ability of traditional indicators to detect differences in management between SHPP pairs was inconsistent and was exceeded by several of the decomposition indicators, specifically rooibos tea and cotton.

2.5.1. Relationships between decomposition, traditional soil health indicators, and yield

Crop yield is the top priority for most producers, and it can be argued that it is an integrative indicator of soil health in and of itself. Examining the relationship between traditional and decomposition indicators and maize yield across many sites in Iowa, US allowed me to look at how yield and both types of indicators relate over a somewhat narrow range of climates and soil types. I was surprised to find little correlation between yield and traditional soil health indicators – the exception being PMN, which showed a positive correlation with yield. Measures of N-supplying power, like PMN, are often better related to maize yield and also N demand than inorganic N which is just a ‘snapshot’ of plant-available N (Franzluebbers,

2018; Hurisso et al., 2018; McDaniel and Grandy, 2016). Despite few correlations between traditional soil health indicators and maize yield, decomposition of the teas, both early (4 d) and late (130 d) were positively correlated with maize yield. There are several possible explanations for these observed relationships. Climate has large influence over both decomposition (Meentemeyer, 1978) and crop growth (Ray et al., 2015); so it is likely that favorable climatic conditions for decomposition are also favorable for crop growth. However, air temperatures and precipitation were not drastically different among locations, especially in 2018 where most sites were within 14 km to each other. After climate, N-supplying power of the soil is the next most likely factor influencing the positive decomposition-yield relationship. Both plants and soil decomposers are often N-limited (Kibblewhite et al., 2008), especially early in decomposition when C:N of residues is wider (Sollins et al., 2009), so soils with higher N-supplying power (from SOM) also likely have higher yields.

While the traditional soil health indicators used here are the most common, they are not exhaustive, and have methodological limitations discussed in other papers (Broos et al., 2007; Gil-Sotres et al., 2005; Paz-Ferreiro and Fu, 2016). These soil health indicators used in this study are all measures of C and N either in microbial biomass, microbial activity, labile sources of energy and N in the soil, or a combination of one or more. In one way or another they are used to make inferences about soil microbial biomass or activity. In addition, they are less expensive and more convenient to measure than most other soil biological measures. I hypothesized that decomposition, which is heavily regulated by soil biota and labile resources available to them, would positively correlate with these traditional indicators. This was not supported by the evidence – with some exceptions (Table 2.7, Fig. S2.5 and S2.6). Of the 20 total instances of correlation, 16 were negative. In spring, very few traditional soil health

indicators correlated with decomposition. MBC and PMN in spring positively correlated with later stage (130 d) decomposition of green and rooibos tea, respectively (Table 2.7, Fig. S2.5). This may have to do with resource availability over time. In the autumn, when plant available N is more scare, soils with greater microbial activity or endogenous labile SOM might be able to mine more N from the remaining high quality green tea (C:N=12) than less active soils. On the other hand, rooibos tea has a C:N ratio above the threshold of N-limitation for decomposers (C:N~30-35, Bonanomi et al., 2017). Soils with higher PMN have more labile N available for soil organisms, which could allow for more successful use of carbon from the rooibos tea. In autumn, only POXC correlated positively with later stages of both green and rooibos tea decomposition (Table 2.7, Fig. S2.6). A likely explanation for this is that later stages of decomposition are often limited by labile C in mineral soil. A general principle in nearly all litter decomposition studies is that the C:N ratio of the litter narrows as decomposition proceeds (Aber and Melillo, 1980; Gosz et al., 1973; Manzoni et al., 2010); therefore, it makes sense that later stages of decomposition would be enhanced by greater concentration of labile C, which is assessed here through oxidization with permanganate.

In contrast to my hypothesis, I found a consistent and strong negative relationship between decomposition and many soil health indicators – especially in the autumn soil sample and especially between PMC and decomposition of both teas. This unexpected, consistent negative relationship may be due to the 'resource island' effect often cited in soil ecology (Bonanomi et al., 2017; Burke et al., 1998; Craine et al., 2007; Knorr et al., 2005). In other words, healthier soils rich in labile C or N might promote decomposition of substrates that are limited by these elements, but have no effect or even decrease decomposition of substrates that are not limited. Both teas have relatively narrow C:N ratios (13 and 51) compared to cotton and

birch (Table 2.2). It is possible that the greater quantity and quality of labile resources available to the microbial community in healthy soils decreased their need to use the buried household items as a C or N source, and that greater decomposition occurred primarily in nutrient poor soil where there was less endogenous labile SOM. This might also explain the positive correlation between yield and tea decomposition since there is some evidence that plants and microorganisms compete for nutrients; specifically N (Inselsbacher et al., 2010; Kaye and Hart, 1997; Schimel and Bennett, 2004). If crops were outcompeting microbes for N, then microbes might be forced to break down the household items for nutrients instead, accounting for both the negative relationship between microbial measures and the positive relationships between yield and tea decomposition.

2.5.2. Treatment effects on decomposition and traditional soil health indicators, and comparisons of signal-to-noise

The other aspect of comparison between traditional and decomposition indicators was examining how well each was able to detect differences between SHPP and conventional agriculture practices. The SHPPs used in this study were chosen because there is evidence to suggest that they affect both traditional indicators of soil health as well as decomposition (Barel et al., 2019; Chahal and Van Eerd, 2018; Culman et al., 2010; Gul et al., 2015; Idowu et al., 2009; Ladd et al., 1994; McDaniel et al., 2014b, 2014a; Wardle et al., 1999). Both traditional and decomposition indicators showed high variability (Fig. 2.3). In other words, most of the indicators were noisy. This is a common obstacle for soil health tests due to the complexity of factors affecting soil processes of interest. Results of both traditional and decomposition indicators are products of the soil microclimate, which is impacted by a host of abiotic factors and complex biotic interactions. It has been demonstrated that soil biology and activity is highly variable in time and space (Cambardella et al., 1994; Wick et al., 2002). This variability exists

even within a field, and it can be difficult to tease apart natural fluctuations (noise) from actual differences in soil health due to management practices (signal). In Iowa, these difficulties might be exacerbated by the high background levels of SOM – which range from 2-8%. Soil organic matter is central to many SES and central to soil health (Doran and Zeiss, 2000; Romig et al., 1995; Rottler et al., 2017); and in Iowa, it is possible even for soils under poor management to contain enough SOM to support some SES like provisioning plant growth, especially with the help of inputs to mask deficiencies (Fenton et al., 2005)

Most decomposition indicators showed increased decomposition with the SHPP compared to its paired control except for perennial cropping (Figure 2.2). Perennial cropping was the SHPP where the most differences were detected for decomposition indicators, but there was more decomposition in the control than in the SHPP for all significant indicators except for cotton. This is most likely due to soils under the perennial crop, *Miscanthus giganteus* being both cooler and moister than the control treatment (Figs. S2.2 and S2.3). Thus, conditions for decomposition might have been more favorable in the control plots for this one SHPP. The greater trend in SHPPs causing increases in decomposition aligns with previous work. It has been demonstrated that rooibos tea decomposes more quickly in cover cropped plots than fallow plots (Barel et al., 2019), and that the longer soil receives no till management, the more decomposition there is of both green and rooibos tea (Houben et al., 2018).

While the exact reason for enhanced decomposition from SHPPs is unknown, it is likely one or more of the following: increases in soil microbial biomass, community composition, or availability of soil resources (Culman et al., 2010; Holland and Coleman, 1987; Wardle et al., 1999). Enhanced decomposition may, at first glance, seem counterintuitive to building soil health. However, recent literature on SOM formation, and the role of microorganisms in the

process, suggest that greater decomposition and stable SOM formation occur together (Castellano et al., 2015; Cotrufo et al., 2015, 2013), and analysis of the origin of stable SOM material indicates that microbial biomass is a large contributor (Kallenbach et al., 2016; Liang et al., 2017). Also, the efficiency of converting organic materials to stable SOM has been shown to increase with what are considered regenerative soil practices like organic (Kong and Six, 2010) and green manure addition (Garcia-Franco et al., 2015), indicating that soil health and decomposition are congruent.

Traditional indicators overall did not consistently detect treatment differences, though spring MBN was the traditional indicator that detected differences most often (Fig. 2.1). Microbial biomass is related to important SES like nutrient supplying power (Li et al., 2004), and long-term C storage (Kallenbach et al., 2016), which are also influenced by SHPPs (Gul et al., 2015; Ladd et al., 1994; Moore et al., 2014; Salinas-Garcia et al., 1997). These relationships might explain the detecting power of MBN. Decomposition indicators were also inconsistent overall, but early stages of rooibos tea decomposition (4 and 7-d) were more often able to detect differences between SHPPs (Figure 2.2). The success of this indicator is likely the result of N availability early in the growing season. As mentioned earlier, soil microbes will often preferentially break down residue that will supply a limiting nutrient (Craine et al., 2007). Springtime in agroecosystems is characterized by greater amounts of plant available and labile N from previous years residue slowly decomposing (Bonde and Rosswall, 1987; McDaniel and Grandy, 2016; Salinas-Garcia et al., 1997). This would make for more C-limited rather than N-limited conditions for soil microorganisms. Therefore this might explain the greater positive response to wider C:N substrate like rooibos tea but only early in the growing season. As the

season progresses, this enhanced decomposition in the SHPP dissipates and shows more of a negative affect compared to the control (Fig. 2.2).

In order to compare the signal-to-noise between traditional and decomposition indicators, I compared their CVs (Figs. 2.3 and 2.4), and p-values derived from comparing estimated SHPP means to their controls for each treatment and site (Fig. 2.5). The two teas had the most consistently low CVs overall (Figure 2.3) for several reasons. Tea likely demonstrated low CVs in part because it is in contact with the soil in situ for a longer period of time than traditional indicators, so it has a better chance to equilibrate and reduce variability. Also, compared to cotton and birch, there was a smaller mean and range in tea due to restricted access of soil fauna (because of the 0.25 mm mesh size). Having a smaller portion, and average size, of the soil community take part in decomposition may narrow the coefficient of variation but have other artifacts as discussed in litter mesh literature (Bokhorst and Wardle, 2013; Bradford et al., 2002; Wieder and Lang, 1982). The mesh around the tea, and removing soil contamination to get ash-free dry mass may also have eliminated some of the variation seen with cotton and birch. Not to mention, being in a mesh bag makes it easier to retrieve an intact sample of tea as well. All of these factors probably contributed to the difference in CV between the teas and cotton and birch. If researchers are interested in using these materials, I would suggest decomposing them in mesh bags. Not being able to have an 'off-the-shelf' decomposable material, however, inconveniences any researcher or citizen scientist.

To examine signal and noise, I plotted percent difference in estimated means due to SHPP against average coefficient of variation for each combination of site, SHPP, and indicator (Fig. 2.4), and plotted p-values for the mean treatment differences (Fig. 2.5). Early stages of tea decomposition were again some of the most sensitive indicators, with a high signal and low noise

(Fig. 2.4). Cotton was also highly sensitive (Figs. 2.4 and 2.5), but it has both a high signal and a high noise possibly due to the difficulty of collecting an intact sample. MBC, MBN, and PMC all exhibit some instances of high signal to noise, particularly in the spring samples. This confirms that measures of microbial biomass (MBC&MBN) or activity (PMC) tend to be sensitive indicators (Dou et al., 2008; Powlson et al., 1987; Wardle et al., 1999).

While the coefficient of concordance permutation test did not show statistical evidence that certain indicators were consistently better at detecting treatment difference than others when all indicators were considered, ranking each indicator within SHPPs and overall was another qualitative way of demonstrating that short incubations of tea, cotton, and several spring traditional indicators were most often able to detect treatment differences.

2.6. Conclusions

Inexpensive, simple, yet scientifically robust measurements of soil health are needed to encourage monitoring and adoption of SHPPs. Here I used a representative area of a major maize-soybean production state in Midwestern U.S., with eight long-term experiments contrasting SHPPs to conventional management, in order to compare decomposition with traditional soil health indicators. My findings show that they were somewhat related, although in unexpected ways. Further research should delve into the mechanisms that drive the common negative relationship between traditional soil health indicators and decomposition found here.

Since decomposing these household items is much less expensive than measuring each of the traditional soil health indicators, the most important question to answer might be: is decomposing these household items at least as good an indicator of differences between known SHPPs and predictors of soil ecosystem services? This answer is a clear yes. Decomposition better-predicted maize yield compared to traditional soil health indicators ($p<0.001$–0.222

compared to p = 0.005–0.965). Furthermore, decomposition showed comparable, if not lower with respect to tea decomposition, variability compared to traditional soil health indicators (average tea CV = 11% compared to average traditional indicator CV = 25%). Decomposing household items also showed a greater ability to detect differences among soil health practices, by having a greater 'signal-to-noise' ratio than traditional soil health indicators. Seventy-eight percent of the indicators that fell above the median signal but below the median noise were decomposition indicators. Early stages of decomposition of tea (4- to 7-d) in pre-made nylon mesh bags and bleached cotton without mesh bag performed especially well. Considering the much lower resource requirements for decomposition versus traditional soil biological health indicators, I recommend using rooibos tea incubations of 4-7 days as an indicator. I also recommend further fine-tuning decomposition of household items as an easily-accessible and scientifically robust method of measuring soil health. Decomposition of household items shows great potential as a soil health indicator to further our understanding of the effects of management practices on soil health, and to engage land managers in citizen scientists.

2.7. Figures

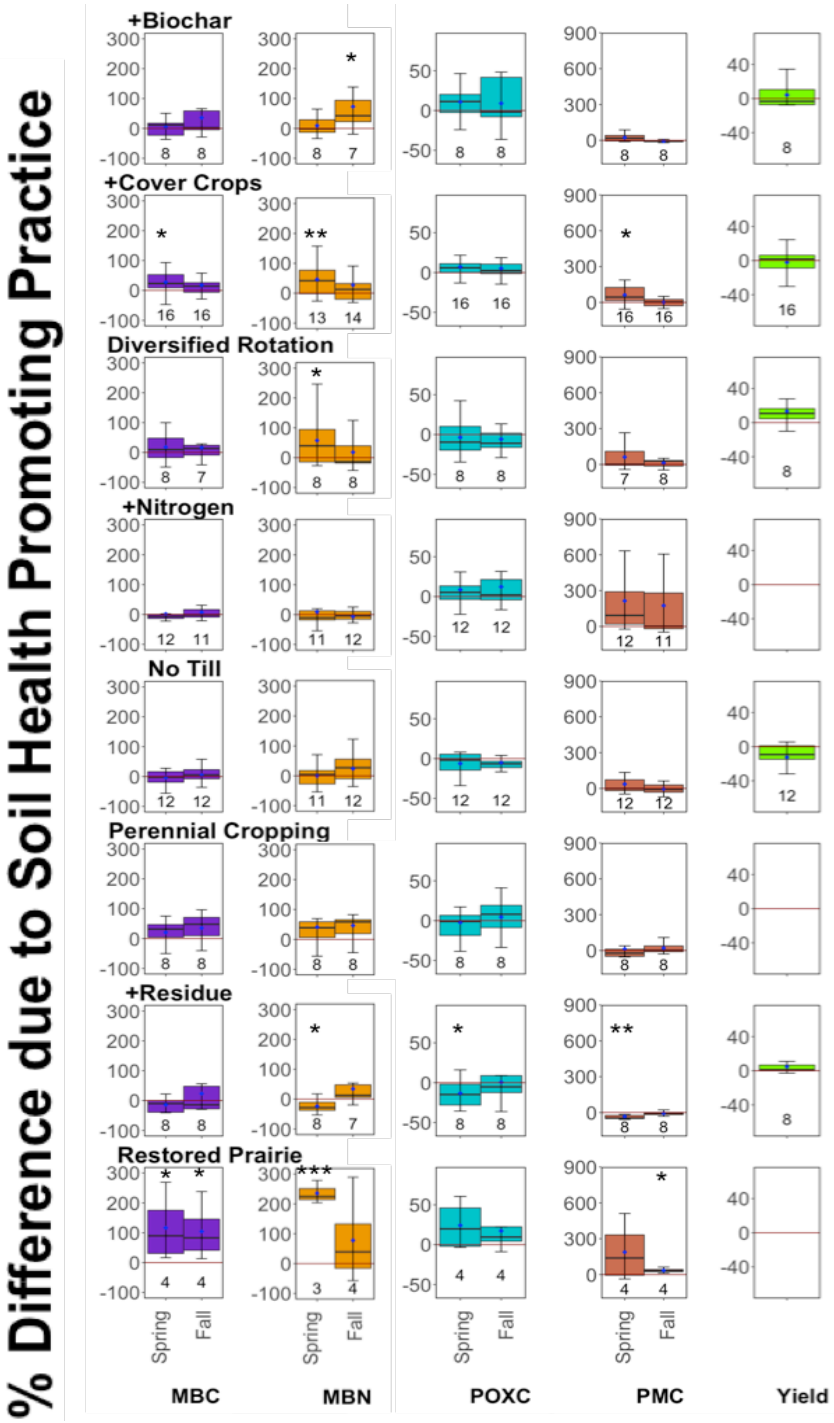

Figure 2.1. The effect of soil health promoting practices (SHPP, Table 2.4) on traditional soil health indicators (Microbial biomass C (MBC) and N (MBN), permanganate oxidizable C (POXC), potentially mineralizable C (PMC) and N (PMN)). Data shown as percent difference due to SHPP for each soil health indicator collected in both spring and autumn. Asterisks indicate significant difference from 0 (*p≤0.05, **p≤0.01, ***p≤0.001). Outliers have been removed and sample size is printed below each boxplot.

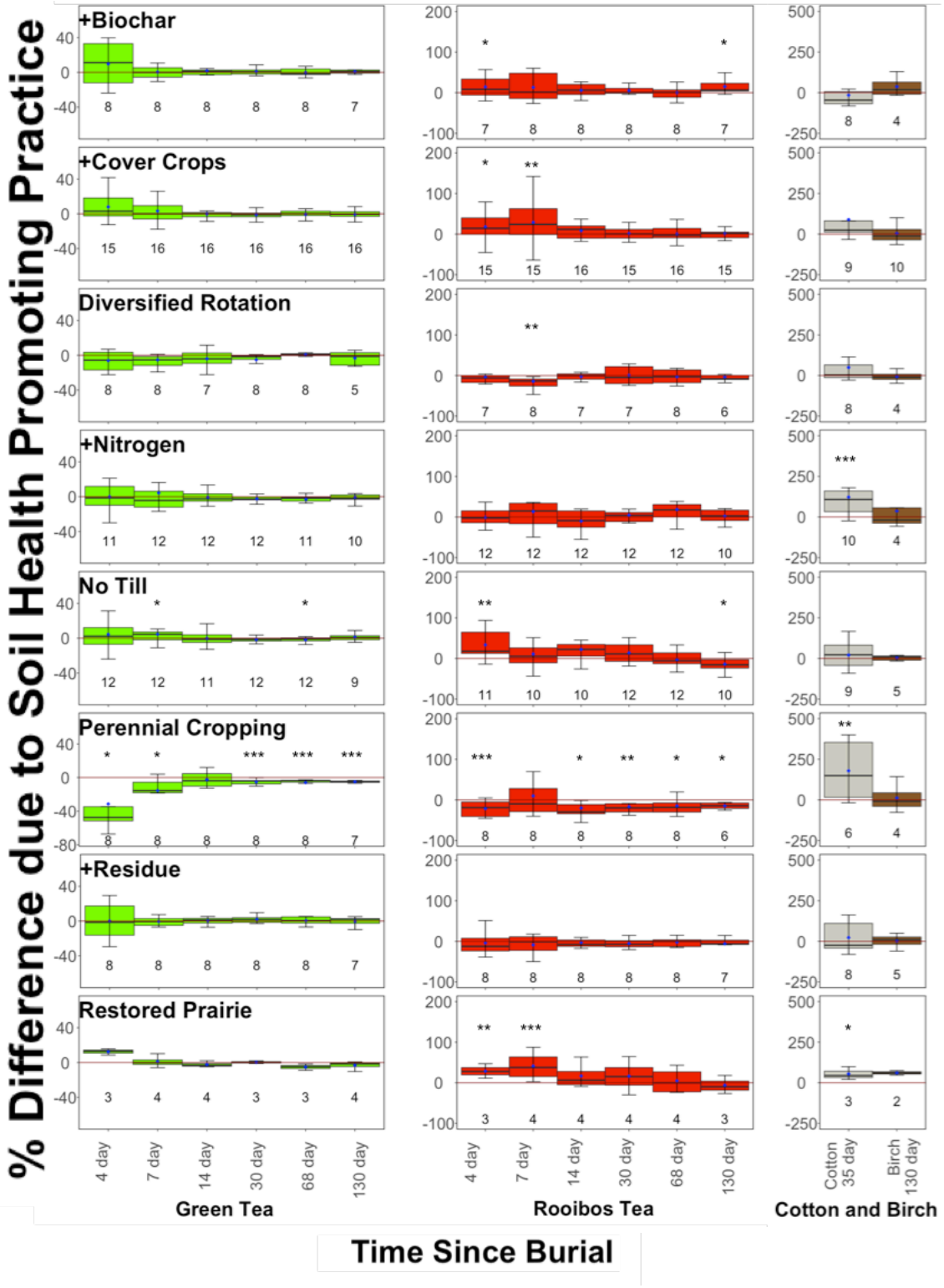

Figure 2.2. The effect of soil health promoting practice (SHPP, Table 2.4) on decomposition indicators. Data shown as percent difference due to SHPP for each soil health indicator. Asterisks indicate significant difference from 0 (*p≤0.05, **p≤0.01, ***p≤0.001). Outliers have been removed and sample size has been printed below each box

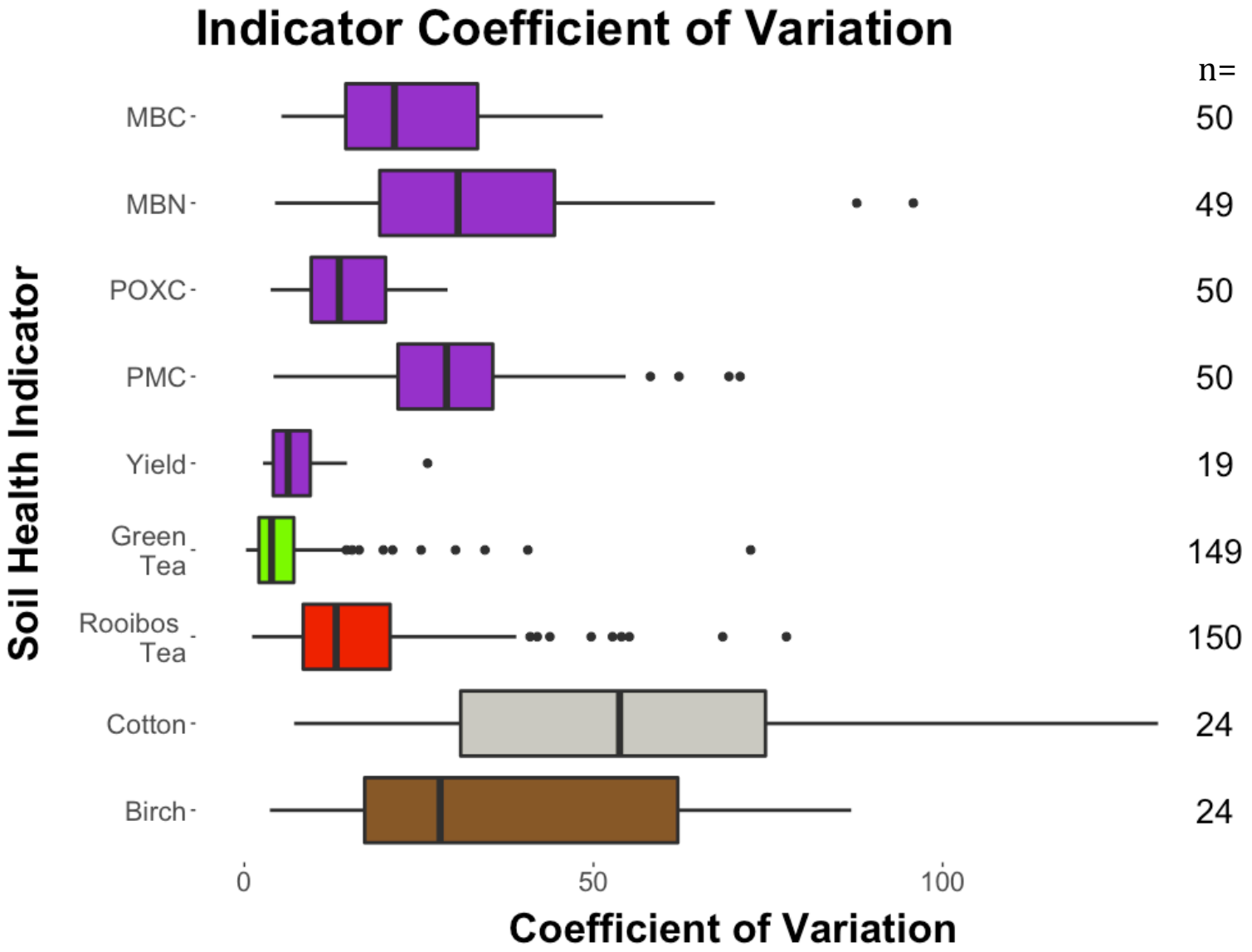

Figure 2.3. Boxplots showing coefficients of variation for each traditional and decomposition soil health indicators. Left whisker is 10th percentile, left edge of box is 25th percentile, bold line is median, right edge of box is 75th percentile, and right whisker is 90th percentile. Outliers (indicated by dots) are values greater than 1.5*IQR. Sample size (n) for each test is on the right.

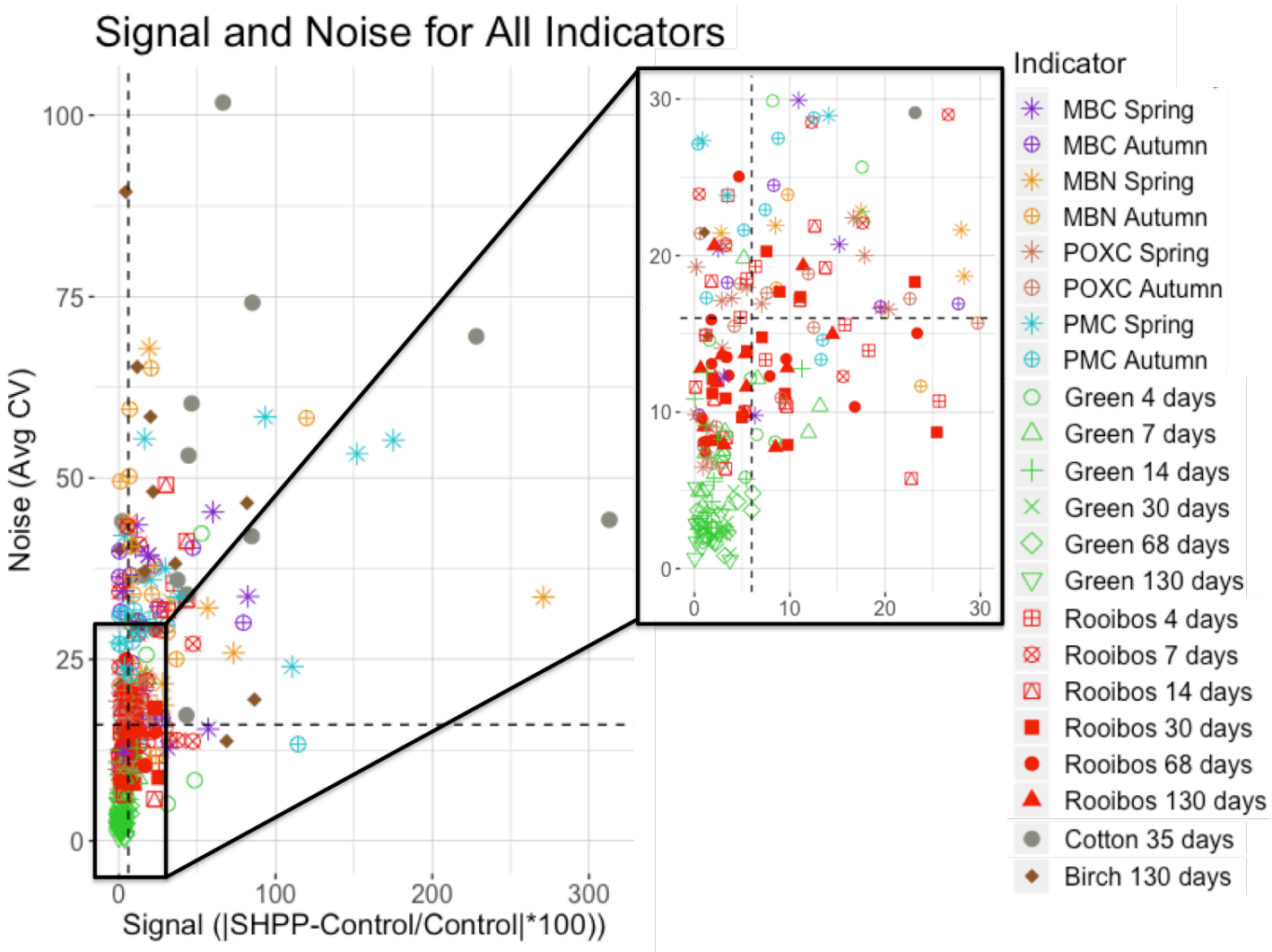

Figure 2.4. 'Signal' regressed against the 'noise'. Signal is percent difference in indicator response due to soil health promoting practice (SHPP) compared to conventional management practice (or control). Noise is the average of both control and SHPP coefficients of variation (CV). Dashed lines represent median signal and noise. Points towards the bottom right of the graph have the highest signal-to-noise ratio.

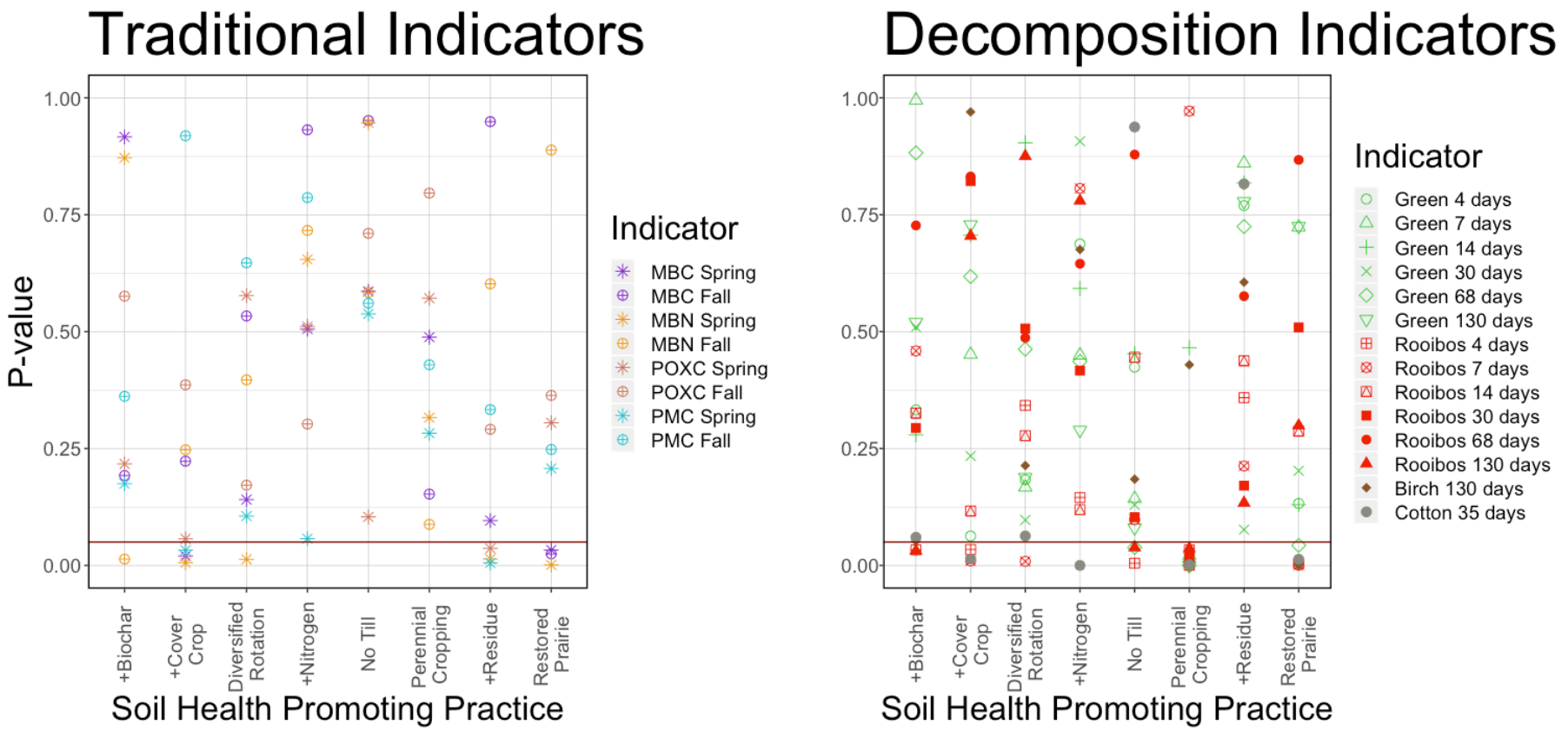

Figure 2.5. P-values from analysis of variance between soil health promoting practice (SHPP) and conventional management practice (control) for traditional (Microbial biomass C (MBC) and N (MBN), permanganate oxidizable C (POXC), potentially mineralizable C (PMC) and N (PMN), *left panel*) and decomposition (*right panel*) soil health indicators. P-values are a measure of signal-to-noise ratio, with lower p-values indicating greater signal-to-noise. ANOVA was conducted using *emmeans* package in R (Lenth, 2019).

Tables 2.8.

Table 2.1. Summary of the traditional indicators of soil health measured and the process or pool of nutrients in the soil they represent.

Traditional Indicator	Unit	Pool or Process Measured
Microbial Biomass Carbon	mg C/kg dry soil	Pool of C stored in microbial biomass, living SOM
Microbial Biomass Nitrogen	mg N/kg dry soil	Pool of N stored in microbial biomass, living SOM
Permanganate Oxidizable Carbon	mg C/kg dry soil	Pool of chemically labile, or active C, includes C available to microorganisms
Potentially Mineralizable Carbon	μg CO_2-C/Kg dry soil	Process of microbial respiration, or respiration potential, pool of C available for microbial metabolism
Potentially Mineralizable Nitrogen	mg N/kg dry soil	Process of microbial net N mineralization, or mineralization potential, pool of N in labile SOM

Table 2.2. Mean and standard deviation (n=4) of chemical parameters for decomposition substrates.

	Green Tea *(Camellia sinensis)*	Rooibos Tea *(Aspalathus linearis)*	Cotton (*Gossypium hirsutum)*	Birch (*Betula spp*.)
Chemical Parameter	Mean ± Standard deviation			
Total Fiber (%)	15.93 ± 1.42	57.60 ± 2.65	92.82 ± 5.05	91.86 ± 0.63
Hemicellulose (%)	2.06 ± 0.89	6.90 ± 2.93	2.46 ± 2.50	22.28 ± 2.49
Cellulose (%)	10.00 ± 1.19	31.66 ± 0.60	90.59 ± 4.32	59.90 ± 2.15
Lignin (%)	4.06 ± 0.72	17.38 ± 2.55	BD†	7.74 ± 3.28
Nitrogen (%)	3.73 ± 0.04	0.96 ± 0.03	0.11 ± 0.01	0.09 ± 0.01
Carbon (%)	47.69 ± 0.31	48.90 ± 0.31	42.16 ± 0.09	46.33 ± 0.13
C:N (unitless)	12.78 ± 0.08	50.77 ± 1.23	399.85 ± 30.04	508.96 ± 47.54

† Below detection. Three of four values were below detection limit, one sample was 0.21%

Table 2.3. Management summary for long-term ISU research site used in 2018 experiment. All sites were planted between 4/27/18-5/18/18 and harvested between 10/4/18-10/30/18. Continued on page 64.

Long-term Experiment Name	Fertilizer Source	Fertilizer Rate	Tillage	Year Established	Paper
Gilmore city Agriculture Drainage and Water Quality (ADWQ) Research and Demonstration Site	Anhydrous Ammonia	168 Kg/ha N	Chisel plow	2010	Qi et al 2011a
Marsden Farm	MESZ, MOP, Elemental S, UAN-32	4 year rotation: 43 Kg N/ha, 39 Kg P/ha, 84 Kg K/ha 2 year rotation: 79 Kg N/ ha, 39 Kg P/ha, 84 Kg K/ha	Cultivator	2002	O'Rourke et al 2006
Boyd Farm	5-10-5, 32% UAN	160 Kg N/ha, 11 Kg P/ha, 6 Kg K/ha	none	2001	Moore et al 2014
Sorenson Cover crop Experiment	DAP, potash, urea	114 Kg N/ha, 112 Kg P/ha, 123 Kg K/ha	Strip-till	2017	
Comparison of Biofuel Systems (COBS)	MESZ, MOP, S, UAN-32	Fertilized Prairie: 60 Kg/ha N, 39 Kg/ha P, 84 Kg/ha K Corn: 170 Kg/ha N, 39 Kg/ha P, 84 Kg/ha K	None	2008	Liebman et al 2008
Iowa State University Agronomy and Ag. Engineering Research Farm Biochar experiment	32% variable rate UAN	Variable N	Chisel plow	2007	Rogovska et al 2016

Table 2.3. Management summary for long-term ISU research site used in 2018 experiment. All sites were planted between 4/27/18-5/18/18 and harvested between 10/4/18-10/30/18. Continued from page 63.

Iowa State University Agronomy and Ag. Engineering Research Farm Tillage experiment	MESZ, potash, 32% UAN	92 Kg/ha N, 39 Kg/ha P, 79 Kg/ha K	Chisel plow	2002	Al-Kaisi et al 2014
Neely-Kinyon Farm	Conventional plots: 32% UAN Organic plots: chicken manure	Conventional plots: 54 Kg N/ha, Organic plots: 6427 Kg chicken manure/ha	Conventional plots: Disk and Cultivator Organic plots: Cultivator, Disk, and Rotary hoe	1998	Delate et al 2016
Sorenson Long-term Assessment Miscanthus Productivity and Sustainability (LAMPS)	28-32% UAN	0 Kg/ha N and 224 Kg/ha N	Conventional Tillage	2015	Boersma et al 2017

Table 2.4. Description of the eight soil health promoting practices (SHPP) examined in this experiment, and the sites at which they are located.

Soil Health Promoting Practice	Control Treatment	Experimental Treatment	Other Details	(n)	Years since establishment
+Biochar	No biochar	8 tons biochar per ha	Both in continuous maize	8	11
+Cover Crop	Winter fallow in a corn-soy rotation	Rye or Perennial Cover crop in a corn-soy rotation	Yield used for the Boyd farm is from 2017	16	2-17
Diversified Rotation	Maize-soy rotation with synthetic N fertilizer	Maize-soy-oat/alfalfa-alfalfa or maize-soy-maize-oat/alfalfa + manure	Neely-Kinyon site received chicken manure, Marsden received composted cattle manure. 32% UAN fertilizer in control plots at both sites	8	16-20
+Nitrogen	No fertilizer	N fertilizer addition as urea	In continuous maize, maize-soy, Miscanthus giganteous, and restored prairie rotations/systems. 60-224 kg N/ha added.	12	3-10
No-Tillage	Chisel plow at 15-20 cm depth	No-tillage	Maize-soy and maize-maize-soy rotations. One site with and without cover crop.	12	8-16
Perennial Cropping	Continuous maize	*Miscanthus giganteous*	Miscanthus established in 2015	8	3
+Residue	No residue	100% of residue left on field	Continuous maize (with and without biochar)	8	11
Restored Prairie	Maize-soy rotation	Restored prairie	Prairie stand harvested for biomass yearly	4	10

Table 2.5. Summary statistics of decomposition and traditional soil health indicators and other ancillary soil properties taken at the beginning and end of the 130-day decomposition incubation. Continued on page 67.

Soil Property	Units	Mean	Standard Deviation	Min	Lower Quartile	Median	Upper Quartile	Max
Microbial Biomass Carbon (MBC)	mg/Kg dry soil	307.7	136.0	97.1	206.5	279.3	390.0	720.1
Microbial Biomass Nitrogen (MBN)	mg/Kg dry soil	39.2	17.7	2.3	26.7	35.6	48.7	96.4
Permanganate Oxidizable Carbon (POXC)	mg/Kg dry soil	542.5	154.7	115.0	462.5	554.8	642.9	933.1
Potentially Mineralizable Carbon (PMC)	ugCO_2 C/ g dry soil	79.4	35.9	7.2	51.6	76.2	101.6	174.6
Potentially Mineralizable Nitrogen (PMN)	mg/Kg dry soil	51.3	35.7	0.4	21.0	29.2	84.2	144.8
Maize Yield	Mg/ha	11.8	4.0	2.3	10.2	11.5	13.7	18.6
Soybean Yield	Mg/ha	3.8	0.7	2.3	3.3	3.9	4.3	4.6
Gravimetric Water content	% water	0.2	0.0	0.1	0.2	0.2	0.3	0.3
Bulk Density (0-3")	g/cm^3	1.2	0.1	0.9	1.1	1.2	1.3	1.4
Bulk Density (3-6")	g/cm^3	1.3	0.1	1.1	1.3	1.3	1.4	1.6
pH	pH	6.6	0.8	4.7	6.1	6.6	7.1	8.3
Nitrate-N	mg/Kg dry soil	2.5	5.7	0.0	0.6	0.8	1.2	36.8
Ammonium-N	mg/Kg dry soil	11.1	12.3	0.1	1.7	5.6	16.7	53.2
Total Inorganic N (Nitrate+Ammonium)	mg/Kg dry soil	12.8	15.7	0.1	2.1	5.9	16.9	77.6
Water Holding Capacity	% water holding capacity	70.6	9.4	47.8	64.9	70.6	76.0	91.4
Total Carbon	% C by weight	2.8	0.9	1.3	2.2	2.7	3.3	5.7
Total Nitrogen	% N by weight	0.2	0.1	0.1	0.2	0.2	0.3	0.5
Soil Temperature	°C	21.9	5.5	5.3	19.6	22.9	25.0	77.9
Soil Moisture	% water by volume	20.6	7.6	6.5	15.0	19.8	25.2	47.7
Green Tea 4-day	% mass loss	33.5	15.3	5.1	20.8	29.5	48.3	68.0
Green Tea 7-day	% mass loss	48.3	7.0	27.9	43.3	47.8	54.3	61.9
Green Tea 14-day	% mass loss	60.8	7.5	39.0	55.8	61.9	67.1	72.7
Green Tea 30-day	% mass loss	71.2	3.9	58.7	69.2	71.8	74.0	78.0
Green Tea 68-day	% mass loss	75.2	3.2	67.6	73.6	75.3	77.4	84.9
Green Tea 130-day	% mass loss	80.1	3.6	71.8	77.6	79.5	82.6	89.3

Table 2.5. Summary statistics of decomposition and traditional soil health indicators and other ancillary soil properties taken at the beginning and end of the 130 day decomposition incubation. Continued from page 66.

Rooibos Tea 4-day	% mass loss	11.3	7.8	1.6	4.6	8.7	17.7	31.8
Rooibos Tea 7-day	% mass loss	11.7	5.6	1.6	7.0	10.0	16.2	24.8
Rooibos Tea 14-day	% mass loss	18.0	5.5	6.7	13.0	18.2	22.2	28.9
Rooibos Tea 30-day	% mass loss	26.8	6.2	14.1	21.6	26.2	31.3	44.1
Rooibos Tea 68-day	% mass loss	37.4	7.4	21.2	31.8	36.6	42.6	55.5
Rooibos Tea 130-day	% mass loss	47.6	9.2	31.5	39.9	47.8	54.6	68.6
Cotton	% mass loss	18.3	11.5	0.9	9.4	15.0	26.3	54.4
Birch	% mass loss	30.8	16.3	0.0	16.4	34.6	42.7	61.3

Table 2.6. Summary of comparisons between traditional indicators and yield, and decomposition indicators and yield. Indicators that positively correlate with yield are highlighted in blue, and those that negatively correlate with yield are highlighted in red. Correlation coefficient (R) included to indicate strength and directionality of relationship.

	Trad. Indicator	n	R	p-value	Decomposition Indicator	n	R	p-value
Spring	MBC	44	0.007	0.965	Green 4-d	**43**	**0.553**	**<0.001**
	MBN	39	0.014	0.933	Green 130-d	41	0.301	0.056
	POXC	44	-0.070	0.653	Rooibos 4-d	**43**	**0.600**	**<0.001**
	PMC	44	-0.107	0.489	Rooibos 130-d	38	0.292	0.075
	PMN	**14**	**0.683**	**0.007**	Cotton	27	0.243	0.222
	IN	44	-0.025	0.874	Birch	20	-0.360	0.119
Fall	MBC	43	-0.119	0.447				
	MBN	41	-0.184	0.251				
	POXC	44	-0.032	0.838				
	PMC	44	-0.118	0.445				
	PMN	**13**	**0.726**	**0.005**				
	IN	44	-0.255	0.095				

Table 2.7. Summary of comparisons between traditional indicators and decomposition indicators. Indicators that positively correlate with each other are highlighted in blue, and those that negatively correlate with each other are highlighted in red.

		Green 4-d			Green 130-d			Rooibos 4-d			Rooibos 130-d			Cotton			Birch		
	Trad. Indicator	n	R	p-value	n	R	p-value	n	R	p-value	n	R	p-value	n	R	p-value	n	R	p-value
Spring	MBC	73	0.035	0.769	68	0.219	0.073	73	-0.121	0.309	65	0.001	0.995	36	0.057	0.740	26	0.152	0.459
	MBN	68	0.055	0.653	63	0.149	0.243	68	-0.094	0.448	60	0.001	0.995	33	0.100	0.581	23	0.132	0.547
	POXC	74	-0.062	0.602	69	0.137	0.261	74	-0.083	0.483	66	-0.128	0.306	36	0.022	0.897	26	0.259	0.201
	PMC	**74**	**-0.265**	**0.022**	69	-0.208	0.087	**74**	**-0.342**	**0.003**	**66**	**-0.254**	**0.040**	36	0.227	0.183	26	0.095	0.645
	PMN	36	0.049	0.777	34	-0.021	0.907	36	-0.313	0.063	**33**	**0.346**	**0.049**						
Fall	MBC	**73**	**-0.311**	**0.007**	68	-0.083	0.503	**73**	**-0.414**	**<0.001**	**65**	**-0.274**	**0.027**	35	-0.328	0.054	25	-0.195	0.350
	MBN	68	-0.236	0.053	63	0.018	0.890	**68**	**-0.331**	**0.006**	60	-0.076	0.562	32	-0.316	0.078	26	-0.170	0.449
	POXC	73	0.093	0.432	69	0.220	0.070	73	0.044	0.710	**66**	**0.246**	**0.047**	36	-0.087	0.615	26	0.091	0.658
	PMC	**74**	**-0.346**	**0.003**	69	-0.175	0.151	**74**	**-0.377**	**0.001**	**66**	**-0.323**	**0.008**	36	0.123	0.474	26	0.054	0.792
	PMN	35	-0.209	0.228	33	-0.085	0.639	35	-0.293	0.088	32	-0.038	0.836						

Table 2.8 Mean and standard errors for soil health promoting practices effects on decomposition and traditional soil health indicators for 2018†. Continued on page 71.

		Biochar		Cover crop		Diversity of Rotation		N effect	
Test	Units	No biochar	+Biochar	No cover	Cover	Maize-soybean	Diverse	No N addition	N addition
Microbial Biomass Carbon (MBC)	mg C/kg dry soil	203±15	224±16	**201±11**	**236±15**	250±19	281±22	362±25	368±125
Microbial Biomass N (MBN)	mg N/kg dry soil	30±3	39±3	**28±2**	**35±2**	30±3	35±3	44±4	44±4
Permanganate Oxidizable C (POXC)	mg C/kg dry soil	556±22	596±26	501±17	525±15	596±26	551±20	627±30	667±21
Potentially Mineralizable C (PMC)	μg CO_2-C/ g dry soil	81±6	84±6	53±4	59±4	58±7	70±7	50±7	60±6
Green 4 day	% mass loss	48±3	51±2	48±2	51±2	37±7	33±6	39±4	41±4
Green 7 day	% mass loss	55±1	55±1	54±2	55±1	50±1	47±2	47±3	48±3
Green 14 day	% mass loss	68±1	69±1	66±1	66±1	61±2	61±3	63±2	64±2
Green 30 day	% mass loss	74±1	75±1	73±1	72±1	74±3	70±1	72±1	72±1
Green 68 day	% mass loss	76±1	76±1	74±1	74±1	76±0	77±1	75±1	74±1
Green 130 day	% mass loss	85±1	85±1	82±1	81±1	82±1	78±2	82±1	81±1
Rooibos 4 day	% mass loss	**18±2**	**21±1**	**17±2**	**20±2**	14±2	12±2	16±2	15±2
Rooibos 7 day	% mass loss	16±1	18±1	**14±1**	**18±2**	**12±2**	**10±2**	15±3	15±2
Rooibos 14 day	% mass loss	24±1	26±1	22±1	23±2	22±4	17±2	22±3	19±1
Rooibos 30 day	% mass loss	31±1	32±1	33±2	33±2	26±3	24±3	28±1	26±1
Rooibos 68 day	% mass loss	42±2	41±1	41±2	41±2	38±3	36±3	37±2	36±2
Rooibos 130 day	% mass loss	**54±3**	**60±1**	55±2	55±2	52±4	52±3	48±3	47±3
Cotton	% mass loss	25±4	16±3	15±5	27±5	26±5	27±7	**10±2**	**23±4**
Birch	% mas loss	36±9	49±3	34±5	34±5	32±7	39±3	22±5	17±4

† Bold pairs are significantly different ($p<0.05$)

Table 2.8 Mean and standard errors for soil health promoting practices effects on decomposition and traditional soil health indicators for 2018†. Continued from page 70.

		No Till		Perennial crop		Residue		Restored Prairie	
Test	Units	Chisel Plow Tillage	No Tillage	Maize	Miscan-thus	No Residue	+Residue	Maize-soybean	Prairie
Microbial Biomass Carbon (MBC)	mg C/kg dry soil	240±15	236±17	316±24	386±38	224±14	203±17	**232±34**	**419±27**
Microbial Biomass N (MBN)	mg N/kg dry soil	30±3	31±2	37±3	50±6	39±3	30±3	27±9	47±5
Permanganate Oxidizable C (POXC)	mg C/kg dry soil	582±12	549±18	693±27	684±32	613±18	539±27	543±49	625±20
Potentially Mineralizable C (PMC)	µg CO_2-C/ g dry soil	54±4	54±4	73±7	71±8	93±5	72±6	64±11	98±15
Green 4 day	% mass loss	41±3	42±3	**41±2**	**27±6**	50±2	49±3	48±2	53±2
Green 7 day	% mass loss	**52±2**	**55±2**	**46±2**	**39±3**	55±1	55±1	56±1	56±1
Green 14 day	% mass loss	64±2	65±1	62±2	60±2	68±1	69±1	70±0	68±1
Green 30 day	% mass loss	73±1	72±1	**75±0**	**71±1**	74±1	75±1	69±2	72±1
Green 68 day	% mass loss	**75±1**	**74±1**	**77±0**	**73±1**	76±1	76±1	74±3	72±1
Green 130 day	% mass loss	81±1	83±1	**84±0**	**80±1**	85±1	85±1	83±2	79±2
Rooibos 4 day	% mass loss	**11±1**	**15±2**	**12±1**	**9±1**	21±2	19±1	**21±1**	**26±2**
Rooibos 7 day	% mass loss	11±1	13±1	9±1	9±1	18±1	16±2	**16±1**	**22±1**
Rooibos 14 day	% mass loss	18±2	20±1	**22±4**	**16±1**	25±1	25±1	20±2	23±2
Rooibos 30 day	% mass loss	27±2	29±1	**28±1**	**23±2**	32±1	31±1	29±4	32±2
Rooibos 68 day	% mass loss	37±2	37±2	**38±3**	**31±1**	42±2	41±1	45±3	46±4
Rooibos 130 day	% mass loss	**54±2**	**49±2**	**46±2**	**40±2**	59+2	54±3	64±11	56±2
Cotton	% mass loss	18±3	20±6	**7±3**	**17±3**	21±4	20±4	**20±5**	**37±6**
Birch	% mas loss	37±2	31±6	16±4	13±3	41±8	34±8	19±4	37±2

† Bold pairs are significantly different ($p<0.05$).

Table 2.9. Indicators ranked based on p-value within each soil health promoting practice and overall.

Overall Rank	Soil Health Indicator	Signal-to-Noise Rank (out of 22) +Biochar	+Cover crop	Diversified Rotation	+Nitrogen	No Till	Perennial Crop	+Residue	Restored Prairie
1	PMC Spring	6	4	5	2	12	14	1	10
2	Rooibos Tea 4 day	3	5	13	4	11	4	12	3
3	Cotton 35 day	4	13	3	1	19	5	19	4
4	MBN Spring	19	1	2	13	16	15	2	2
5	Rooibos Tea 14 day	11	8	12	3	3	10	13	12
6	Green Tea 30 day	15	10	4	19	10	1	4	9
7	Rooibos Tea 7 day	14	2	1	18	9	22	8	1
8	POXC Spring	8	6	18	10	1	20	3	14
9	Green Tea 4 day	12	7	9	14	8	7	17	8
10	Green Tea 130 day	16	18	10	5	4	2	18	20
11	MBC Spring	21	3	6	21	15	19	5	6
12	Green Tea 7 day	22	14	7	9	2	9	21	19
13	Rooibos Tea 130 day	2	16	20	16	20	11	6	13
14	Rooibos Tea 30 day	10	19	17	7	22	6	7	17
15	MBN Autumn	1	11	14	22	14	12	10	22
16	POXC Autumn	17	12	8	6	18	21	9	15
17	Birch 130 day	5	22	11	15	5	16	15	18
18	Green Tea 14 day	9	17	21	11	6	18	20	7
19	Green Tea 68 day	20	15	15	8	17	3	16	16
20	Rooibos Tea 68 day	18	20	16	12	7	8	14	21
21	MBC Autumn	7	9	22	20	21	13	22	5
22	POXC Autumn	13	21	19	17	13	17	11	11

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CHAPTER 3. CONCLUSION

This study shows compelling rationale (Chapter 1) and evidence for (Chapter 2) use of household items to measure soil health. Currently, researchers are exploring soil health tests that integrate the physical, chemical, and biological components of soil, as a need for reliable indicators of soil health has been well-demonstrated (Doran and Parkin, 1994; Idowu et al., 2009; Morrow et al., 2016). However, the majority of soil health indicators currently available are not accessible to the average land manager. In order to increase interest and participation in managing soils for sustainability, this is a gap that needs to be bridged. Decomposition is a likely candidate for such a role due to its strong relationship with soil microorganisms, and ecosystem services (e.g. nutrient cycling, organic matter accumulation, etc., Cotrufo et al., 2013; Strickland et al., 2009; Wardle et al., 1999), both of which are integral to soil health.

Past work has illuminated the relationships between microorganisms, residue quality, and decomposition. Soil biota are sensitive to change in agricultural systems (Barel et al., 2019; Gul et al., 2015; Morrow et al., 2016); and along with climate and residue quality, they determine the course of decomposition (Bonanomi et al., 2017; McDaniel et al., 2014a; Wickings et al., 2012). Together, these links indicate that decomposition can be used as a proxy for microbial activity and soil ecosystem services. One of the advantages that decomposition has over measuring these things directly is its ease of use. Decomposing a common substrate and measuring its mass loss requires fewer resources and is easier to interpret than many traditional ways of measuring soil health. The other advantage of using decomposition is that it is an integrated measure over time, compared to the ‘snapshot’ given by traditional soil sampling.

I compared the decomposition of four common household items to several traditional indicators of soil microbial biomass and activity, and labile nutrients. I found that traditional and

decomposition indicators were often negatively related when relationships were present, indicating that household items may only experience high amounts of decomposition when other sources of nutrients are lacking. When comparing the ability of traditional and decomposition indicators to detect differences in management by comparing treatment means and variability, I found that most indicators were inconsistent. However, decomposition performed at least as well as traditional indicators if not better in many cases (Figs. 2.1, 2.2, 2.5). Early stage rooibos tea decomposition in particular was the most successful of any indicator at detecting treatment difference.

Taking into account the relative resources required for traditional and decomposition indicators and their abilities to detect management differences, it is clear that decomposition of a common substrate should be considered as a soil health indicator. In addition to being scientifically robust, it has greater potential to reach wider audiences than some traditional soil health indicators. Future work should focus on fine-tuning the method, making recommendations for land managers based on region and goals, and incorporating technology to encourage use and collaboration.

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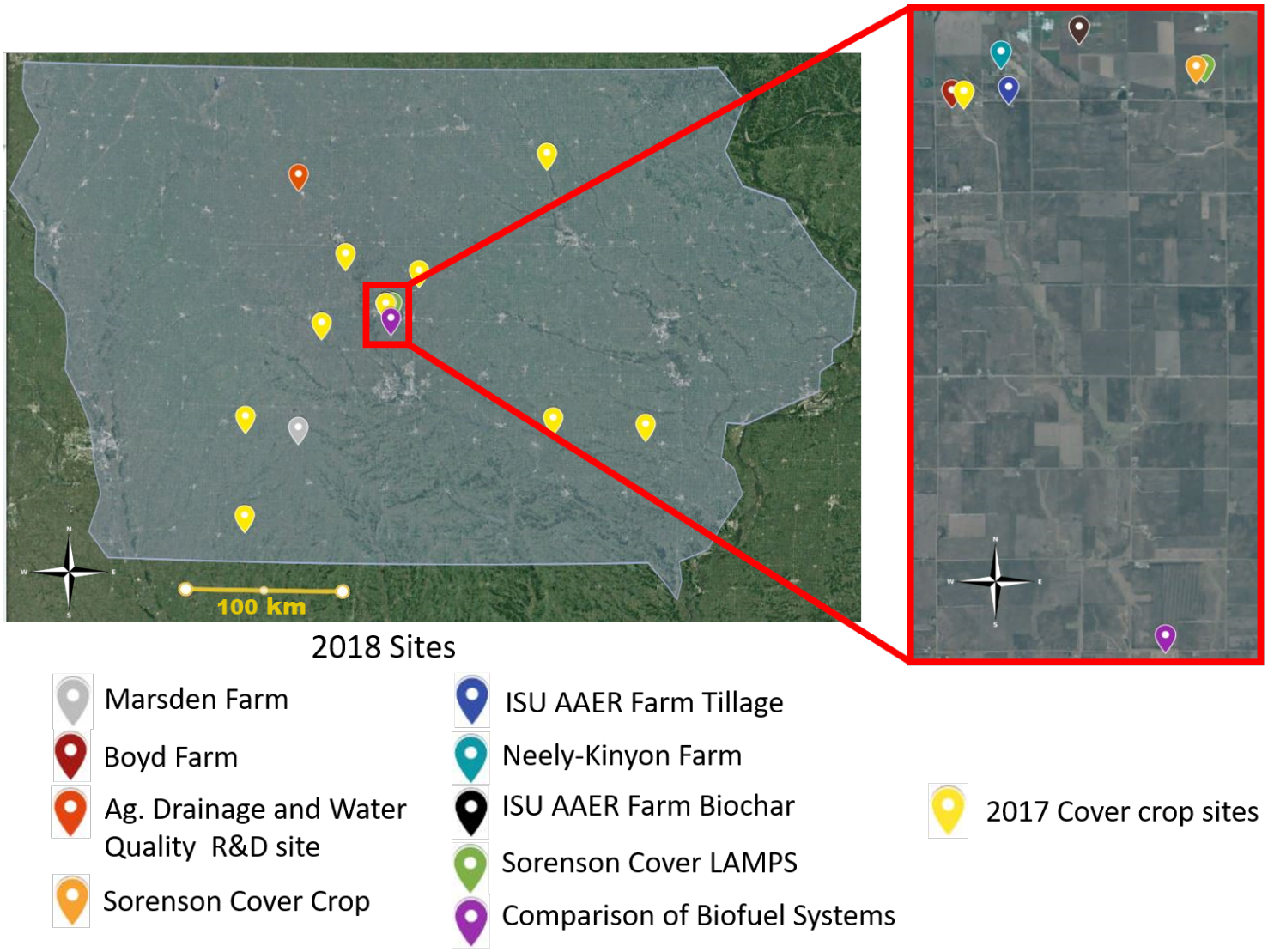

Figure S2.1. Map of the nine Iowa State University-affiliated research sites (long-term experiments) and eight commercial farms with replicated strips.

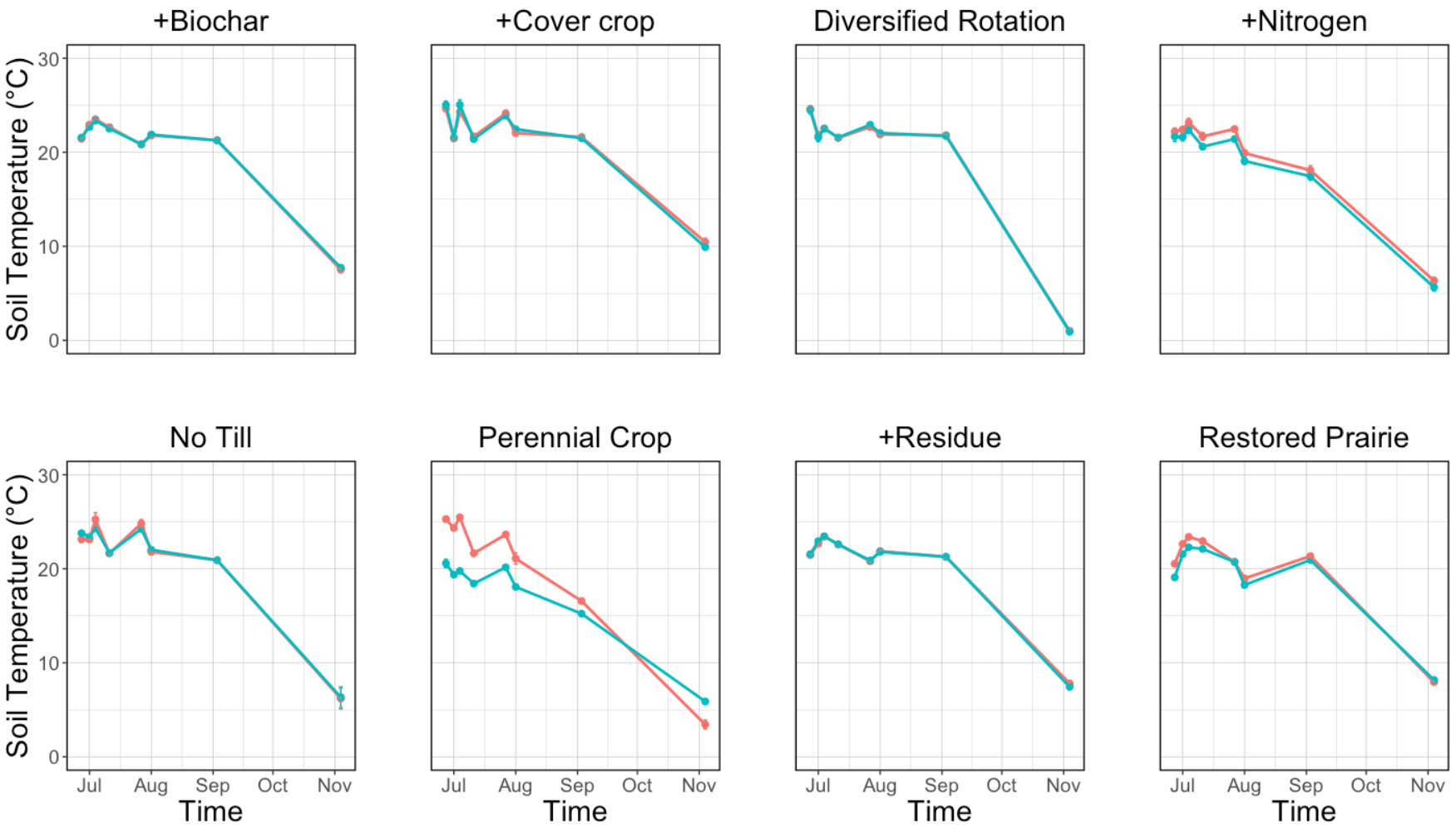

Figure S2.2. Soil temperature measured at 0-11 cm depth over the 2018 growing season under eight soil health promoting practices (Table 2.2). Error bars represent a 95% confidence interval.

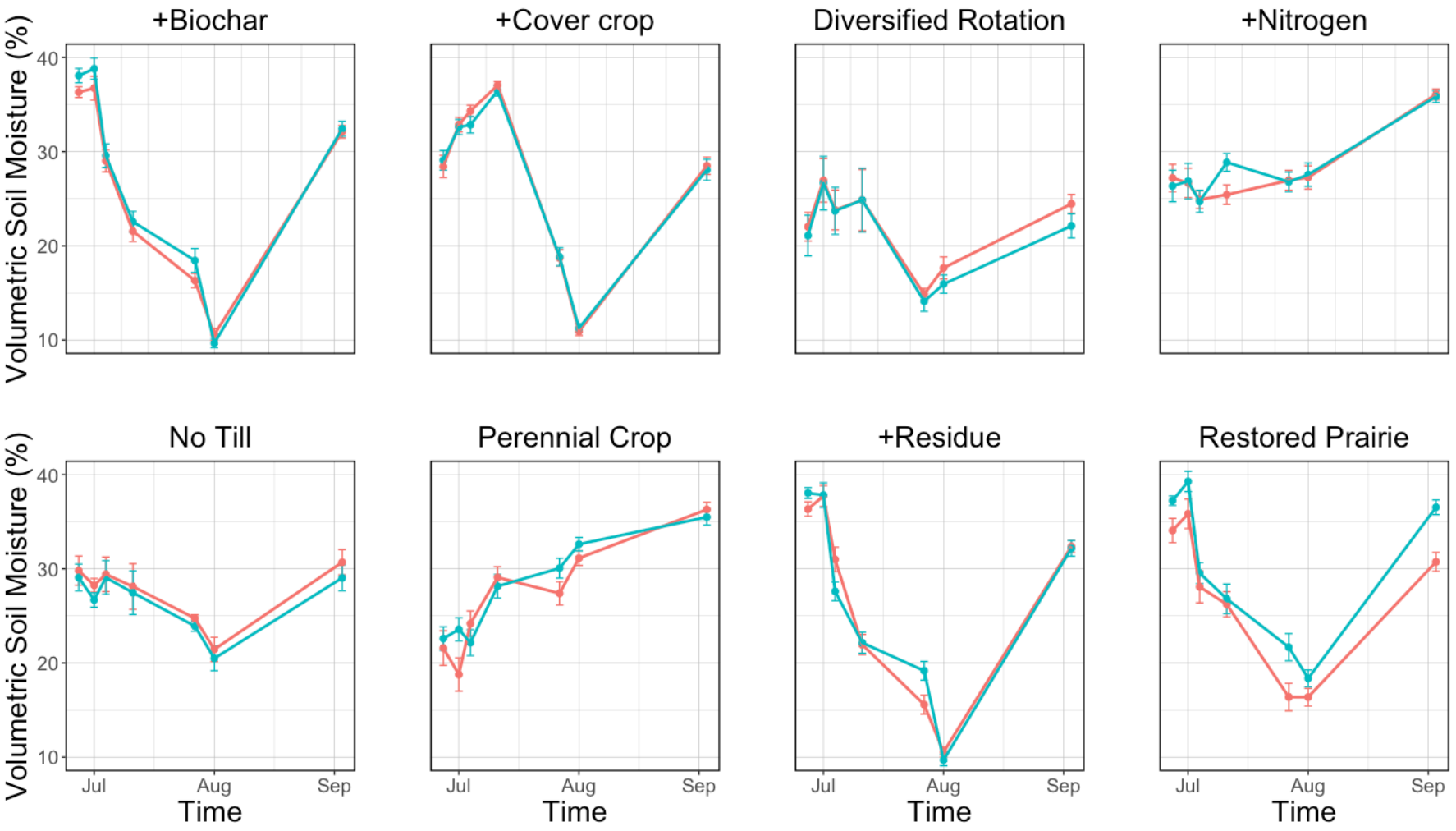

Figure S2.3. Volumetric soil moisture measured at 0-6 cm depth over the 2018 growing season under eight soil health promoting practices (Table 2.2). Error bars represent a 95% confidence interval.

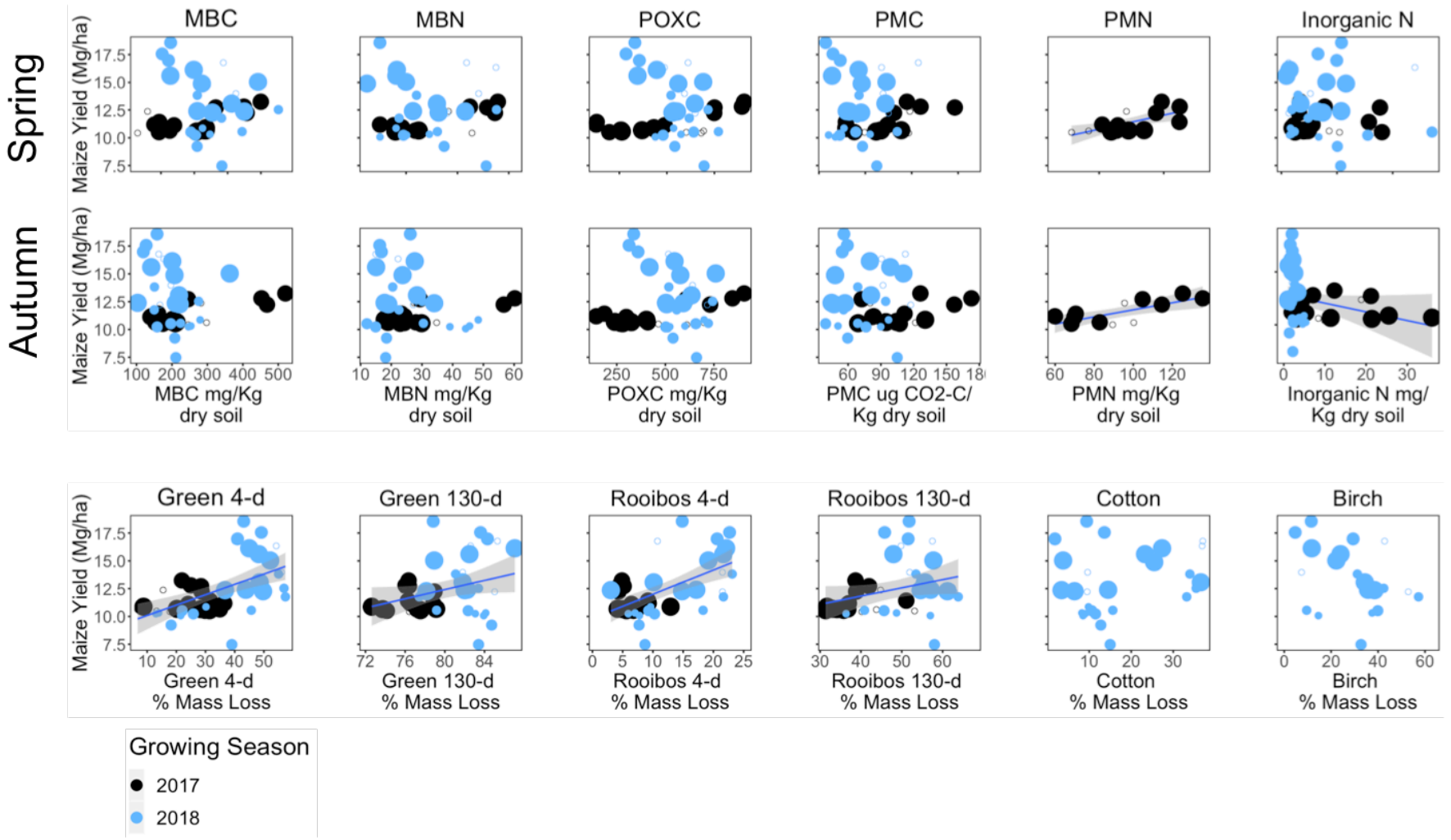

Figure S2.4. Maize yield correlated with traditional (Microbial biomass C (MBC) and N (MBN), permanganate oxidizable C (POXC), potentially mineralizable C (PMC) and N (PMN), *left 2x6 panels*) and decomposition (*right 1x6 panels*) soil health indicators. Maize yield data from 2017 (*black*) and 2018 (*light blue*) years. Nitrogen fertilizer rates shown by bubble size (*see legend*). Spring soil sampling between 6/12/2018 to 7/20/2018, and autumn soil sampling between 10/18/2018 to 11/20/2018. Linear regression and 95% confidence interval shown if p-value <0.1.

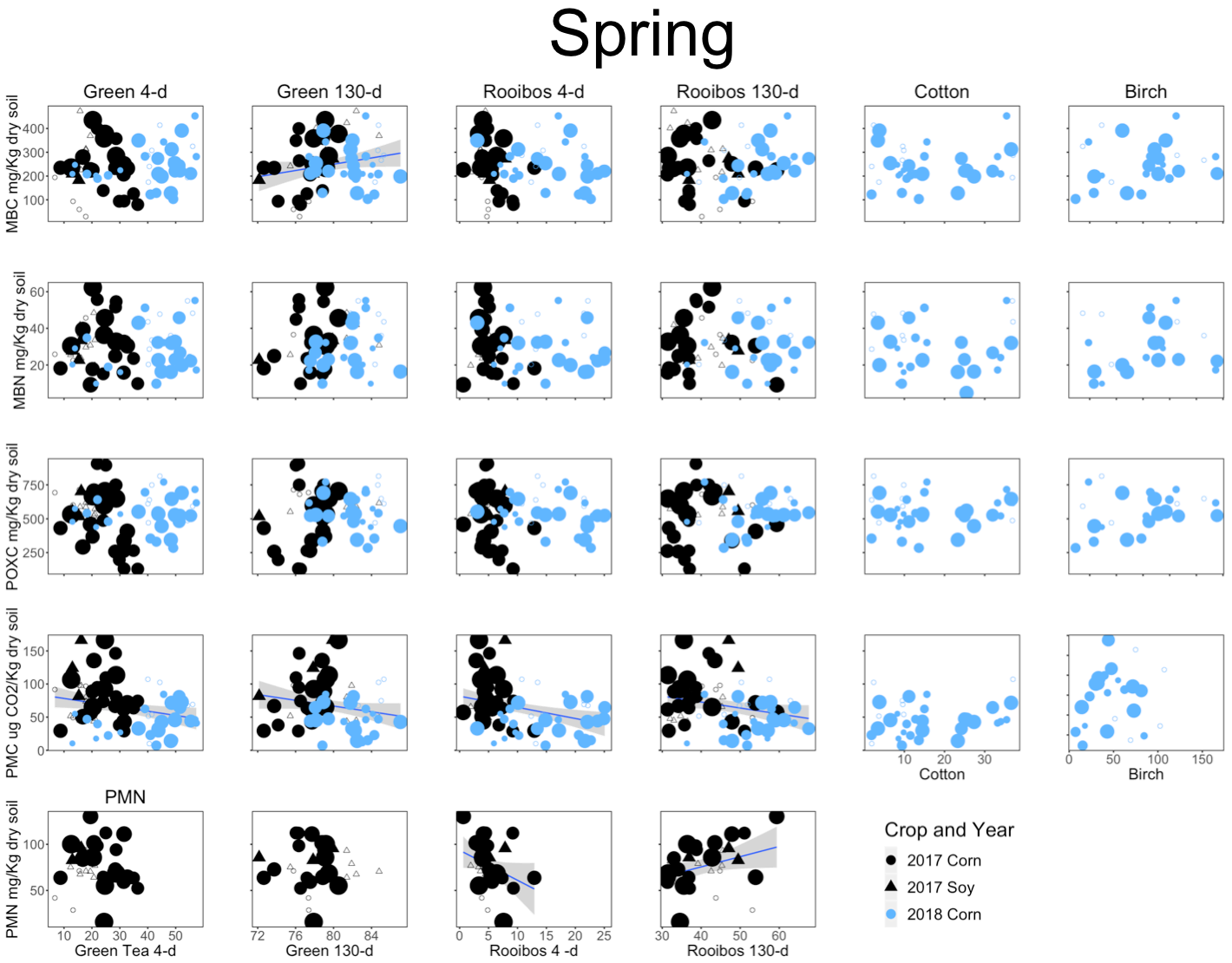

Figure S2.5. Traditional soil health indicators (Microbial biomass C (MBC) and N (MBN), permanganate oxidizable C (POXC), potentially mineralizable C (PMC) and N (PMN)) measured between 6/12/2018 to 7/20/2018 correlated with decomposition with nitrogen fertilizer rate indicated by bubble size (see legend). Linear regression and 95% confidence interval shown if p-value <0.1.

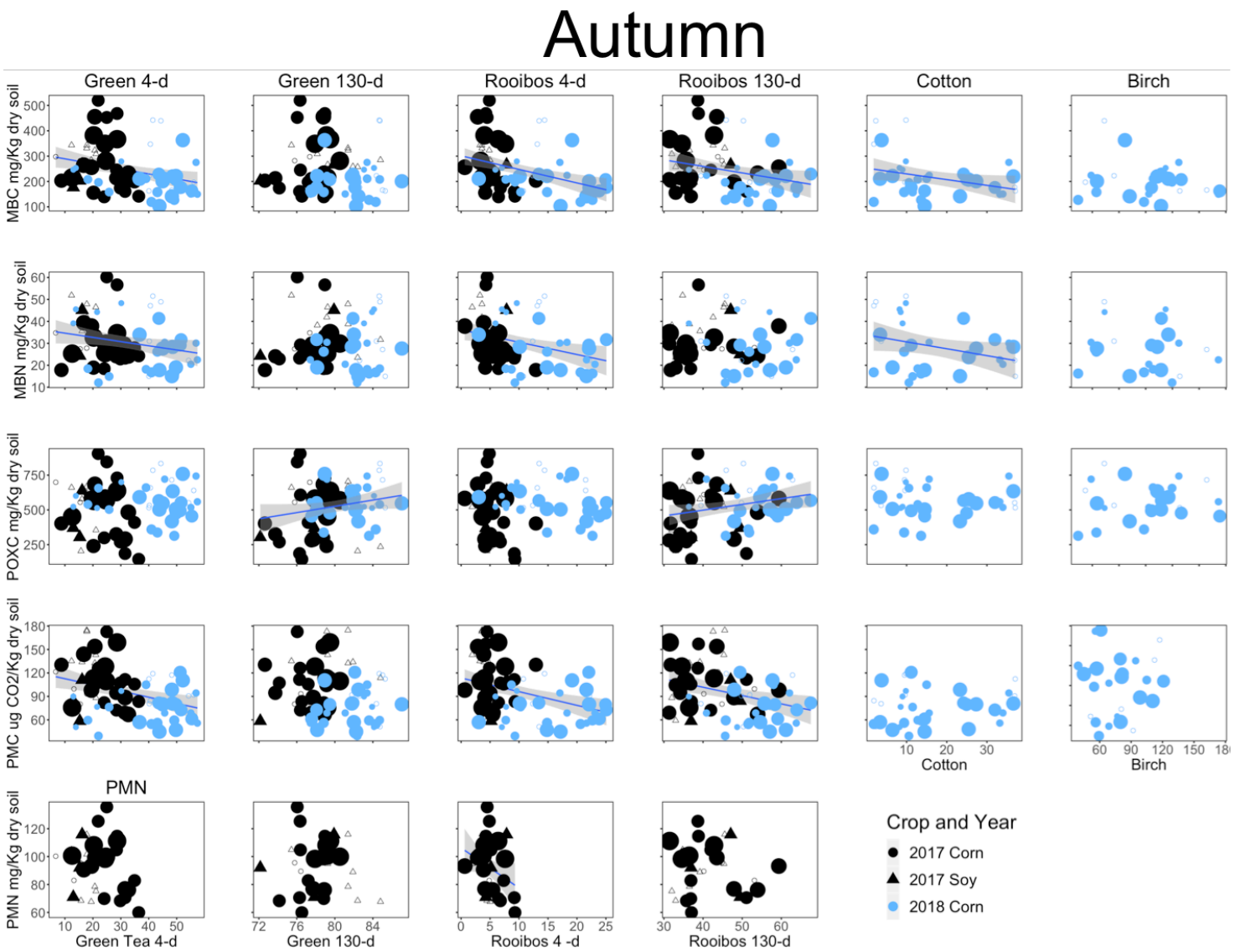

Figure S2.6. Traditional soil health indicators (Microbial biomass C (MBC) and N (MBN), permanganate oxidizable C (POXC), potentially mineralizable C (PMC) and N (PMN)) measured between 10/18/2018 to 11/20/2018 vs. decomposition indicators with nitrogen fertilizer rate indicated by bubble size (see legend). Linear regression and 95% confidence interval shown if p-value <0.1.

Table S2.1. Location, soil series, and climate for 2018 long-term experiments. Continued on page 93.

Site	Location	Coordinates	Soil Series (National Cooperative Soil Survey - USDA)	Mean Annual Precipitation † (mm)	Mean Annual Temperature † (°C)
Gilmore city Agriculture Drainage and Water Quality (ADWQ) Research and Demonstration Site	Gilmore City, IA	42°44' N, 94°29' W	Canisteo Clay loam (Fine-loamy, mixed superactive, calcareous, mesic Typic Endoaquolls) Nicollet Clay loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls)	850	8.3
Marsden Farm	Boone, IA	42°00' N, 93°46' W	Clarion loam (Fine-loamy, mixed, superactive, mesic Typic Hapludolls) Nicollet loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls) Webster silty clay loam (Fine-loamy, mixed, superactive, mesic Typic Endoaquolls)	970	8.7
Boyd Farm	Boone, IA	42°00'N, 93°47' W	Nicollet loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls) Clarion loam (Fine-loamy, mixed, superactive, mesic Typic Hapludolls)	970	8.7
Sorenson Cover crop	Boone, IA	42°00'N, 93°44' W	Webster clay loam (Fine-loamy, mixed, superactive, mesic Typic Endoaquolls)	970	8.7
Comparison of Biofuel Systems (COBS)	Boone, IA	41°55' N, 93°44' W	Nicollet loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls) Webster clay loam Fine-loamy, mixed, superactive, mesic Typic Endoaquolls)	970	8.7
Iowa State University Agronomy and Ag. Engineering Research Farm Biochar experiment	Boone, IA	42°01' N, 93°45' W	Webster silty clay loam (Fine-loamy, mixed, superactive, mesic Typic Endoaquolls) Clarion loam (Fine-loamy, mixed, superactive, mesic Typic Hapludolls) Canisteo silty clay loam (Fine-loamy, mixed superactive, calcareous, mesic Typic Endoaquolls)	970	8.7

Table S2.1. Location, soil series, and climate for 2018 long-term experiments. Continued from page 92.

Iowa State University Agronomy and Ag. Engineering Research Farm Tillage experiment	Boone, IA	42°00' N, 93°47' W	Nicollet loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls) Webster clay loam (Fine-loamy, mixed, superactive, mesic Typic Endoaquolls) Clarion loam (Fine-loamy, mixed, superactive, mesic Typic Hapludolls) Macksburg silty clay loam (Fine, smectitic, mesic Aquertic Argiudolls)	970	8.7
Neely-Kinyon Farm	Green-field, IA	41°16'N, 94°26'W	Nira silty clay loam (Fine-silty, mixed, superactive, mesic Oxyaquic Argiudolls)	900	10.9
Sorenson Long-term Assessment Miscanthus Productivity and Sustainability (LAMPS)	Boone, IA	42°00'N, 93°44' W	Canisteo Clay loam, (Fine-loamy, mixed superactive, calcareous, mesic Typic Endoaquolls) Webster clay loam (Fine-loamy, mixed, superactive, mesic Typic Endoaquolls) Nicollet loam (Fine-loamy, mixed, superactive, mesic Aquic Hapludolls)	970	8.7

† Precipitation and Temperature data from the National Climatic Data Center.

Table S2.2. Location, soil series, and climate for 2017 on-farm trials.

Site	Location	Coordinates	Soil Type (National Cooperative Soil Survey - USDA)	Mean Annual Precipitation † (mm)	Mean Annual Temperature † (°C)
Farm A	Washington, IA	41°18' N 91°48' W	Mahaska (Fine, smectitic, mesic Aquertic Argiudoll)	927	9.7
Farm B	Plainfield, IA	42°53’ N, 92°33' W	Waukee (Fine Loamy over sandy, mixed, superactive, mesic Typic Halpudoll)	884	8.6
Farm C	Jamaica, IA	41°53' N, 94°16’ W	Lester (Fine-loamy, mixed, superactive, mesic Mollic Halpudalfs)	819	9.1
Farm D	Roland, IA	42°12' N, 93°32’ W	Clarion (Fine-loamy, mixed, superactive, mesic Oxiaquic Halpudoll)	881	9.1
Farm E	New Market, IA	40°44’ N, 94°50’ W	Sharpsburg (Fine, smectitic, mesic Typic Agriudoll)	917	9.6
Farm F	Wiota IA	41°19’’ N, 94°50’ W	Marshall (Fine-silty, mixed, superactive, mesic Typic Halpudolls)	937	9.3
Farm G	Boone, IA	42°00’ N, 93°47’ W	Clarion (Fine-loamy, mixed, superactive, mesic Oxiaquic Halpudoll)	974	8.7
Farm H	Rose Hill, IA	41°20’N, 92°30'W	Mahaska (Fine, smectitic, mesic Aquertic Argiudoll)	971	9.6
Farm I	Dayton, IA	42°17'N, 94°06’ W	Marna (Fine, smectitic, mesic Vertic Endoaquolls)	974	8.7

† Precipitation and Temperature data from the National Climatic Data Center.